Models for operational optimisation in a horizontal logistic cooperation

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Dissertation

Models for operational optimisation in a horizontal logistic cooperation

Gain sharing, incentives and multi-level objectives

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Dutch preface

De invoering van lage emissiezones in en rondom grote steden, de kilometerheffing voor vrachtwagens op autosnelwegen en de stijgende energieprijzen zetten de bedrijven onder druk om hun transportactiviteiten steeds efficiënter te organiseren. Daarnaast zorgt het stijgende aandeel van e-commerce, waarbij goederen vaak rechtstreeks bij de klanten thuis geleverd worden, ervoor dat het distributienetwerk fijnmaziger is dan ooit.

De gezamenlijke organisatie van transportactiviteiten wordt gezien als een interessante denkpiste voor het verhogen van de logistieke efficiëntie. In tegenstelling tot traditionele (ad-hoc) bundeling, gaat het bij zulke horizontale samenwerkingsverbanden om lange-termijncontracten tussen verschillende bedrijven, actief op hetzelfde niveau in de supply chain, waarbij de actieve synchronisatie van de goederenstromen tot de creatie van nieuwe synergieën leidt.

Voor het optimaal organiseren van hun transportactiviteiten maken bedrijven gebruik van logistieke planningsalgoritmes, veelal ingebed in gespecialiseerde softwarepakketten. De bestaande algoritmes werden ontwikkeld vanuit de impliciete veronderstelling dat het transport gepland en uitgevoerd wordt door één enkel bedrijf. Dit maakt zulke algoritmes minder geschikt voor het ondersteunen van beslissingen binnen horizontale logistieke samenwerkingsverbanden. Deze doctoraatsthesis heeft tot doel de eerste stappen te zetten in de ontwikkeling van logistieke optimalisatiemodellen en -algoritmes, waarbij meerdere partijen gezamenlijk hun logistieke activiteiten organiseren. De focus ligt op (1) het integreren van allocatiemodellen voor het verdelen van bijvoorbeeld kosten, opbrengsten of middelen onder de betrokken partijen, en (2) het ontwikkelen van optimalisatiemodellen waarin de doelstellingen van zowel de coalitie als de individuale partijen in beschouwing kunnen worden genomen. Beide aspecten worden hieronder verder uitgelicht.

Aangezien alle bedrijven, actief binnen een horizontaal samenwerkingsverband, individuele entiteiten blijven, dienen de kosten en opbrengsten van de gezamenlijke logistieke planning opnieuw herverdeeld te worden. De bestaande allocatiemodellen die hiervoor gebruikt worden variëren van eenvoudige vuistregels tot complexe verdeelsleutels uit de cooperatieve speltheorie en kunnen significant van elkaar verschillen. Dit wordt in deze thesis zowel empirisch als door middel van een theoretische simulatie aangetoond. In tegenstelling tot deze bestaande benaderingen, waarbij veelal gefocust wordt op de *fairness* van iedere methode, wordt in dit werk gebruik gemaakt van incentives om de verschillende allocatiemodellen van elkaar te onderscheiden. Op deze manier kunnen individuele bedrijven aangespoord worden zich flexibel te gedragen ten opzichte van hun samenwerkingspartners. Immers, hoe meer een bedrijf bereid is zich aan te passen aan wat optimaal is voor de coalitie, hoe meer synergie er door de samenwerking gerealiseerd kan worden. Omwille van deze wisselwerking, kan het kostenallocatieprobleem niet afzonderlijk van het logistieke planningsprobleem beschouwd worden.

In hoofdstuk 4 wordt het verband tussen winstverdelingsmechanismen en incentives empirisch bestudeerd. Er wordt een onderscheid gemaakt tussen het verdelen van de winst op dagelijkse basis en periodische winstdeling (bijvoorbeeld wekelijks of maandelijks). Er wordt zowel een rigide als flexibele planning beschouwd. Het verband tussen de performantie van de coalitie (in termen van synergiecreatie), flexibiliteit van de individuele partners en de impact op de kostenverdeling wordt verder theoretisch onderzocht in hoofdstuk 5.

In bestaande logistieke optimalisatiemodellen wordt steeds verondersteld dat de bedrijven, die de krachten bundelen in een horizontaal samenwerkingsverband, enkel één of meerdere gemeenschappelijke objectieven nastreven. Met andere woorden, de individuele belangen van de partijen worden niet rechtstreeks in beschouwing genomen. Deze beperking wordt losgelaten in dit werkstuk en de aanzet wordt gegeven tot de ontwikkeling van logistieke optimalisatiemodellen waarbij objectieven op meerdere niveaus gedefinieerd kunnen worden. Naast het coalitieniveau, worden hier ook de belangen (objectieven) van de verschillende individuele partners meegenomen. Immers, een oplossing die niet door alle partijen als 'optimaal' beschouwd wordt, draagt niet bij tot de langetermijn stabiliteit van de coalitie.

De integratie van zogenaamde partnerobjectieven in logistieke optimalisatiemodellen is het onderwerp van de hoofdstukken uit deel iii van deze thesis. Drie alternatieve benaderingen worden geïntroduceerd: model met coalitie-efficiëntie (hoofdstuk 6), model met partnerefficiëntie (hoofdstuk 6) en een gecombineerd model (hoofdstuk 8). In het eerste model definiëren de coalitiepartners een set objectieven op het niveau van de groep en wordt het logistiek optimalisatiemodel op coalitieniveau opgelost. Op basis van vooraf gedefinieerde verdeelsleutels, wordt de waarde van deze oplossing op de individuele objectieven van iedere partner bepaald, waarna de oplossing geëvalueerd wordt door alle individuele coalitiepartners. Het model met partnerefficiëntie maakt geen gebruik van overkoepelende objectieven op coalitieniveau, maar beschouwt de individuele objectieven van alle partners rechtstreeks in de optimisalisatieprocedure. Een gecombineerd model wordt tenslotte gedefinieerd in hoofdstuk 8. In deze benadering worden beide voorgaande modellen gecombineerd en sequentieel opgelost. Op basis van simulatie-experimenten wordt aangetoond dat individuele bedrijven in vele gevallen hun eigen situatie kunnen verbeteren door af te wijken van de optimale oplossing op coalitieniveau. Deze resultaten benadrukken het belang van de verdeelsleutels en de kennis over de sensitiviteit van een oplossing en mogelijke alternatieven.

Daarnaast levert deze thesis ook een grote bijdrage aan de literatuur rond geclusterde routeplanningsproblemen. Deze recente uitbreiding op het klassiek routeplanningsprobleem waarbij klanten tot vooraf gedefinieerde clusters behoren, wordt uitgebreid besproken in hoofdstuk 7. Dergelijke problemen komen bijvoorbeeld voor in de fijndistributie van online verkoop, waarbij kleine pakketjes bij een groot aantal klanten thuis beleverd dienen te worden. Omwille van de grootte van dergelijke routeplanningsproblemen, wordt in de praktijk vaak gewerkt met 'zones'. In deze thesis wordt een performant algoritme voor het oplossen van dergelijke optimalisatieproblemen voorgesteld, en wordt een nieuwe variant van het probleem gedefinieerd.

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Background, motivation and research goals

1.1 The logistics landscape, facts and figures

In 2014, the transport and storage services sector (third-party logistics) accounted for about €633 billion in Gross Value Added at basic price in the EU-28, which is equivalent to 5.1% of total GVA. Total goods transport activities in the EU-28 amounted to 3524 billion tkm in 2014, from which road transport accounted for 49%. The transportation sector was responsible for around 25% of all green house gas emissions, of which more than 72% is caused by road transportation. (European Commission 2016)

The popularity of the road as main transportation mode can be explained by the increasing pressure for fast (just in time) delivery of small batches, its flexibility and the availability of a dense road network (Vannieuwenhuyse, Gelders, and Pintelon 2003). However, some well known negative externalities caused by road transportation are the increasing congestion and pollution, e.g., green house gas emissions, noise,... (Verhoef 1994). Furthermore, despite its popularity, the usage of trucks still lacks efficiency and sustainability. In 2014 more than one fifth of all trips was performed by empty vehicles (Eurostat 2015). Other studies show that the average fill rate of a truck is below 50% (Boer et al. 2009; Knörr 2008). These numbers clearly show potential for improvement.

1.2 Call for sustainability and supply chain integration

Mainly driven by the continuous innovations in the information and telecommunication industry, the speed at which the world evolves is increasing dramatically. With every product or service only a couple of clicks away, companies are challenged to rethink their supply chain capabilities to accommodate the transition from an industrial to an information technology driven society (Lyon 2013). Raw materials, including fossil fuels, become more scarce and the debate on the relationship between green house gas emissions and climate change is growing. Companies experience an increased pressure towards a more sustainable (often referred to as "green") supply chain management (Srivastava 2007).

Over the last decades, the transportation sector has put an enormous effort into improving the efficiency of its operations. Consider for example the ongoing strive for more fuel-efficient engines or the introduction of the foldable container (reducing both the number of empty movements and the storage cost). Also, the advances in information technology resulted in satellite applications for emergency handling, traffic alerts, road safety and incident prevention (Fremont et al. 2012).

Globalisation, together with the fact that traditional barriers between industries are breaking down, has forced supply chain networks to become more efficient and increase the responsiveness to fast changing technologies and customer demands. To maximise the added value for the end customer, companies should be aware that they no longer compete solely as autonomous entities, but rather as supply chains (Lambert and Cooper 2000). This more integrated view on the supply chain requires companies to interact with other entities. The academic literature usually distinguishes among two main directions of integration (or collaboration): vertical and horizontal.

1.2.1 *Vertical collaboration*

To increase the overall performance of the supply chain, it requires the different entities up- and downstream to synchronise their operations by sharing information. Such a scheme, where collaboration occurs between companies that operate at different levels of the supply chain is referred to as vertical collaboration. (Amer and Eltawil 2014)

Vendor Managed Inventory (VMI) and Cooperative Planning, Forecasting and Replenishment (CPFR) are well known examples of vertical collaboration. In a VMI partnership, the vendor monitors the buyers' inventory levels, taking the responsibility to make periodic resupply decisions (Waller, Johnson, and Davis 1999). CPFR relies on the retail level demand forecast, which is used to synchronise replenishment and production plans throughout the entire supply chain (Attaran and Attaran 2007; Fliedner 2003).

1.2.2 *Horizontal collaboration*

Horizontal collaboration refers to a collaboration between two or more unrelated or competing companies active at the same level of the supply chain (European Commission 2011). By sharing available knowledge, resources, manufacturing capacities or warehouse space, companies are able to create synergies which they could not exploit when working alone (Soosay, Hyland, and Ferrer 2008). In Dyer and Singh (1998) this is referred to as *relational rent*. Horizontal collaboration can be a means to share risk, save costs, increase investments, pool know-how, enhance product quality and variety, and launch innovation faster (European Commission 2011).

Compared to vertical collaboration, the academic literature on horizontal collaboration is rather scarce and it remains less common in practice. However, it is considered a viable way to increase the efficiency and sustainability of the transportation sector by both researchers and practitioners (vanovermeire 2014).

1.2.3 *Lateral collaboration*

A collaboration that combines the capabilities of both the vertical and the horizontal dimension is referred to as lateral collaboration. The synchronisation of multiple shippers and carriers in an effective transportation network can be considered an example of lateral collaboration (Simatupang and Sridharan 2002).

1.3 **Opportunities for collaborative logistics optimisation**

Transportation planning problems, most notably *vehicle routing problems*, have received much attention from the Operations Research community. Many state of the art algorithms have contributed considerably in reducing the number of kilometres driven unnecessarily by transportation companies (Braekers, Ramaekers, and Van Nieuwenhuyse 2015). Traditionally, this logistics optimisation is done for one single transportation company. In part due to ever more powerful optimisation algorithms, however, the potential for individual efficiency improvements have diminished and only relatively small gains remain obtainable. Researchers and practitioners therefore have increasingly searched for optimisation opportunities outside of the realm of individual optimisation. One of the more promising research avenues in the *joint* or *collaborative optimisation* of transportation companies' operational activities (Cruijssen, Dullaert, and Fleuren 2007).

The overall aim of collaborative logistics optimisation is to find and exploit synergies between multiple companies such that a more efficient global transportation planning can be obtained. We assume that these companies (shippers or carriers) are the decision-making entities for what concerns logistics planning. The economies of scale, realized through bundling of goods, might lead to a reduction in the operational cost per load unit. Furthermore, it might facilitate companies to make the shift towards other (more sustainable) transportation modes. Other potential benefits are an increase in the transport frequency or the enlargement of the service area. (Jourquin, Beuthe, and Demilie 1999; Kreutzberger 2008)

The principles of bundling exist already for decades as many companies outsource their logistics to a logistics service provider that takes care of the consolidation. This is however done based on ad-hoc or reactive bundling of orders that happen to have the same delivery date and destination, and can fit together in one truck (Vanovermeire et al. 2014). In this thesis we consider *horizontal logistics cooperation*, which involves companies on the same level of the supply chain jointly organizing their transport. As it requires the commitment of each participating company to organize their transport in such way that bundling opportunities are maximized and pro-actively looked for, it can be considered a more integrated approach and a win-win situation can be obtained. (vanovermeire 2014)

1.4 Contribution of the thesis

In this thesis, logistics planning problems are studied within the context of horizontal logistics cooperation. Compared to (traditional) stand-alone logistics optimisation, the operational planning tends to be considerably more complex for a horizontal logistics cooperation. Partly, this is due to the size of the optimisation problem, which is obviously much larger in a horizontal cooperation. Partly this is due to the multi-partner optimisation context, usually neglected in the literature. We aim at providing both the research community and the interested practitioners with a solid framework for defining, handling and solving collaborative optimisation problems.

Although, in general, an operational perspective is adopted, our findings and developed models are likely to also affect decision-making at tactical level. For example, the selection / definition of a cost (or profit) allocation mechanism occurs typically at tactical level, and will highly impact the outcome of the daily operations for each individual partner in the coalition. In part ii, this interdependency between tactical (partner behaviour and the cost allocation mechanism) and operational level (the routing solution) is studied elaborately. Also in part iii of the thesis, it is shown that these tactical allocation rules largely determine the acceptance of an operational plan by the individual partners. Our models and algorithms can also be used to support decision making at strategic levels through the simulation and comparison of alternative coalition configurations and different supply chain network topologies. These issues are, however, not explicitly addressed throughout this work.

More precisely, the contribution of the research to the field of horizontal logistics cooperation is twofold:

1. Study the role of the cost allocation (or gain sharing) mechanism as an incentive for partners to behave and perform in a way that benefits the group as a whole.

2. The integration of individual partner interests into the global optimisation procedure at the coalition level.

Because of the more operational perspective of the thesis, it is assumed that the coalition is formed upfront and all partners are willing to participate in the collaboration. It is explicitly not questioned how this coalition is formed or whether it would be better to disband the cooperation. Furthermore, we consider all organizational, legal or IT-related issues to be addressed beforehand.

In part i, we introduce the reader to the basic concepts and definitions of horizontal logistics cooperation (**chapter 2**) and cost allocation / gain sharing (**chapter 3**). As horizontal logistics cooperation is a recently emerging topic on the academic research agenda, the existing literature is rather new and exploratory. We provide the reader with an overview on the current state of the art and introduce the terminology adopted in this thesis. The chapter on cost allocation and gain sharing includes an introduction to cooperative game theory after which we elaborate on the existing allocation mechanisms referred to in this thesis: the Shapley value, the Nucleolus, the Equal Profit Method, the Alternative Cost Avoided Method and the volume-based allocation. Furthermore, we will elaborate on the property of individual rationality and propose an algorithm to transform any allocation result to its closest individual rational alternative.

In the second part of this thesis we study how cost allocation or gain sharing mechanisms might provide incentives to the individual collaborating partners. **Chapter 4** studies the link between gain sharing and incentives empirically by performing a simulation study on data obtained from a collaboration of three fresh produce traders at a Belgian fruit and vegetables auction. A distinction is made between allocating the gains on a daily basis (e.g. for each individual transport) or on a periodic basis (e.g. weekly or monthly), and a rigid planning is compared to a more flexible scenario in which a transport can be postponed by one day if that leads to a more profitable logistics planning. The interdependency between the logistics planning and the allocation of costs and benefits is extended further by including also the individual partner behaviour in **chapter 5**. We demonstrate that the efficiency of the global operational plan is highly dependent on the strategic behaviour of the individual partners. This partner behaviour is defined by the height of a compensation cost for not serving some of its customers. By choosing the right cost allocation mechanism, the coalition can implicitly formulate incentives for the partners to behave in a beneficial way. These dependencies are shown and tested by applying them to a collaborative variant of the Selective Vehicle Routing Problem (SVRP).

Although the coalition as a whole should perform as efficient as possible to fully exploit all synergies from the cooperation, all collaborating partners remain independent entities that tend to favour the solution that is best according to their individual objectives. Part iii of this thesis bundles all chapters related to the inclusion of individual partner objectives in the logistics optimisation model. **chapter 6** introduces the difference between coalition objectives and individual partner objectives. When multiple partners, each of which having one or more individual objectives, jointly perform their operational planning, two options arise. A first option is that the coalition first defines a set of global coalition objectives, encompassing all objectives of all partners, then finds a solution or a set of non-dominated (Pareto efficient) solutions for these global objectives, and then divides the objectives (costs) back to the individual partners. We call this approach the *coalition efficiency model*. The second option is to consider all individual partner objectives and find a set of non-dominated solutions for each individual partner, without first aggregating them into coalition objectives. We call this approach the *partner efficiency model*. The merits and drawbacks of both approaches are investigated by applying them to a collaborative variant of the well-known Travelling Salesman Problem with soft time windows (TSPSTW).

Chapter 7 introduces the reader to the Clustered Vehicle Routing Problem (CLUVRP). In this vehicle routing variant, customers are grouped in predefined clusters. An additional constraint imposes that all customers belonging to the same cluster are to be visited sequentially by the same vehicle. The CLUVRP finds it application in, e.g., routing for courier companies where the distribution zone is divided in predefined zones. A fast two-level heuristic solution approach is developed and compared to the state-of-the-art algorithms. In contrast to all other chapters in this dissertation, chapter 7 does not consider any form of horizontal cooperation. However, the developed algorithm is required to tackle the CLUVRP as a subproblem in **chapter 8**, in which we present an integrated solution framework for solving multi-partner logistics problems. The framework combines the coalition efficiency model and partner efficiency model from chapter 6 by sequentially solving two optimisation problems: the Coalition Level Optimisation Problem (CLOP) and the Partner level Optimisation Problem (PLOP).

Finally, our conclusions are summarised and discussed in **chapter 9**.

Part I

CONCEPTS AND DEFINITIONS

2

Horizontal cooperation in logistics

11th century. Northern Germany. *To protect themselves from pirates and to reinforce their market position, merchants involved in long-distance oversea trade start to form associations. Through pooling of their volumes on a shared ship, the operational costs decrease and they are able to buy and sell at larger quantities. Furthermore, they are able to engage more easily in negotiations with the rules who were in control of the ports and towns they travelled to. In the following centuries this network will expand as the councils of the merchants' home towns take control of what is still known today as the* ***Hanseatic League*** *or* ***Hansas****. (Fink 2012)*

Driven by the high energy prices and in the light of the growing debate on sustainability, the transportation sector has taken multiple initiatives to improve the efficiency of its operations. Furthermore, the growing e-business and e-commerce increases the pressure to shorter lead times and the (just-in-time) delivery of small batches. Despite al the effort, large optimisation opportunities still exist today as explained in chapter 1.

A recent trend in logistics is the formation of a so-called *horizontal logistics cooperation (HLC)*. This form of collaboration can be defined as a long-term agreement between companies with similar or complementary transportation needs that aim to exploit synergies by means of active bundling and synchronisation (Vanovermeire et al. 2014). Through better joint use of the available resources, the total logistics cost is likely to decrease while maintaining (or even improving) the service level.

2.1 Proof of concept

In the aviation industry, horizontal collaboration among airlines is a common practice. Through collaboration, airline alliances such as **Skyteam** and **Star Alliance** are able to offer an extensive worldwide network (Cruijssen, Dullaert, and Fleuren 2007). In road transportation, the idea of horizontal cooperation emerged only recently. It was 1993 when eight competitive sweet producers from The Netherlands initiated a collaboration named **Zoetwaren Distributie Nederland**. A decrease in total transportation cost was achieved by consolidating the shipments and thereby reducing the number of truckloads, which at his turn also had a positive effect of the unloading and handling costs (Cruijssen, Dullaert, and Fleuren 2007). Since then, multiple successful implementations of HLC have been described in the literature.

Bahrami (2002) reports on the collaboration between **Henkel** and **Scharzkopf**, two German producers that were able to reduce their total distribution cost by 9.8% trough HLC.

The joint distribution of frozen goods from **Douwe Egberts**, **Unipro** and **Masterfoods** in The Netherlands has resulted in a 30.8% reduction in distance travelled. Furthermore, through optimised bundling, the load factors were increased to over 95% and the number of trucks required dropped by 50%. (Cruijssen et al. 2007)

With more than 60% of their delivery addresses in common, **Kimberly-Clark** and **Unilever HPC** were able to increase the number of delivery days per week by 57% while decreasing the total number of drops by 31% when considering a joint distribution. (Verweij 2009)

To meet the required full truckloads demanded by French retailers when delivering goods to their warehouses, **Mars**, **United Biscuits**, **Saupiquet** and **Wrigley** installed a cooperative VMI system. Furthermore, collaborative deliveries are now dispatched from a shared warehouse. (Guinouet, Jordans, and Cruijssen 2012)

Two pharmaceutical companies, **UCB** and **Baxter**, jointly organise their shipments to Romania. Through HLC, higher load factors combined with the possibility to switch to rail have resulted in a 30% to 50% reduction in green house gas emissions and double-digit cost savings. (vanovermeire 2014)

The web-accessible tool **T-scale** is presented in Hajdul and Nowak (2014). With this application, the authors aim at facilitating and standardising the information exchange between multiple companies for purposes of joint organisation of deliveries. A pilot with ten producers resulted in a 15% cost saving.

Instead of exploiting only the similarity between multiple transportation requests, in some case studies the complementarity of the goods contribute to the success of the cooperation. By combining lightweight and heavyweight products the available vehicle capacity can be filled more efficiently, resulting in high load factors according to both volume and weight limits. Jordans (2011) describes a pilot in which the lightweight products of **Philips** and the heavyweight products of **Hunter Douglas** are transported in a shared truck towards England. Similarly, the co-loading from Czech Republic to Germany of plastic beads bags from **JSP** and heavy metal automotive break disks from **Hammerwerk** results in double-digit savings in CO_2 emissions (Verstrepen and Hooft 2011). Also **Procter & Gamble** bundles its heavy pallets with the lightweight products from **Tupperware** between Belgium and Greece (Macharis et al. 2014).

Besides reporting on the outcome of real implementations, some authors apply simulation techniques to investigate the potential of HLC. These simulations are either based on theoretical test instances — we refer to the work of Cruijssen et al. (2007) and Palhazi Cuervo, Vanovermeire, and Sörensen (2016) — or use available real world data for quantifying the potential of HLC.

Boerema and Groothedde (2001) analysed the shipments of different FMCG manufacturers in The Netherlands (**Albert Heijn**, **Laurus**, **Schuitema** and **Aldi**). Through collaboration and the use of inland barges, a 22% reduction in transportation cost is expected.

In Hageback and Segerstedt (2004), the advantages of co-distribution from 20 suppliers to a sparsely populated area in Sweden are expected to equal a 33% cost reduction. Also in Sweden, a potential cooperation in the forestry sector is studied by Frisk et al. (2010).

Gonzalez-Feliu and Grau (2012) consider the possibility of consolidating the outbound shipments of seven automotive companies in Romania. The active bundling and a shift to rail could reduce the cost and CO_2 emissions by 15% and 40% respectively. In that same paper, a corridor that bundles the transportation flows of six companies between Spain and Germany will also decrease cost by 14% and CO_2 emissions with 17%.

This non-exhaustive list of case studies and simulations clearly shows the true potential of horizontal cooperation in the logistics sector. Through active bundling and the synchronisation of transports of several companies, the number of trucks on the road can be reduced and their fill rate can be increased. By using the available capacities more efficiently, significant savings in cost and CO_2 emissions can be realised while maintaining or even improving the service level.

Multiple initiatives aim at bringing together the peer groups from the industry and catalysing the debate on related topics. The European **CO3-project**[1] unites more than fifty important industrial companies. This project is co-financed by the Directorate-General for Research and Innovation of the European Commission (Cruijssen et al. 2014). Also the European Technology Platform **ALICE**[2], an industry-led stakeholder forum that develops short to long-term research and innovation agendas focuses strongly on the potential of horizontal cooperation in logistics. This project will support, assist and advise the European Commission into the implementation of the Horizon 2020 program in the area of logistics. According to the ALICE vision and mission, the goal is to move towards a *physical internet* in which products and goods are moved around the globe like digital information is doing today through the internet (ALICE 2016).

1 www.co3-project.eu
2 www.etp-logistics.eu

2.2 Terminology

HLC is a rather new research domain. Although more and more academic papers appear in this field, the available literature is still limited and scarce. As there does not exist a common vocabulary on horizontal cooperation yet, the applied terminology might differ slightly between papers or press articles. To avoid misinterpretation, we therefore introduce the vocabulary used throughout this thesis in the current section.

An individual company joining an HLC is referred to as a *partner*. In this thesis we adopt a general view in which it is not necessary to specify at which level of the supply chain the collaboration takes place. This partner can therefore be a shipper (company that wants his good to be transported), a carrier (provides transportation services), a manufacturing plant with its own transportation department, or any other type of company. We only assume that the partner is the main decision maker when it comes to the optimisation of the transport operations.

Multiple partners are said to form a *coalition of collaborating partners* (referred to as a *coalition*). A coalition that includes all collaborating partners in the cooperation is called the *grand coalition*, denoted by N. A subset of these partners is denoted as a *subcoalition* $S \subseteq N$. The number of partners in S can range from 0 up to $|N|$.

For each partner, the individual transportation cost without cooperation is referred to as the *stand-alone cost*. The main motivation for companies to collaborate is the fact that the total transportation cost of the coalition (the *coalition cost*) is lower than the sum of all stand-alone costs of the individual partners. The difference between these costs is called the *coalition gain*. Either the total cost of the coalition or the coalition gain is to be divided among all collaborating partners. By not doing this in a 'fair' way, the coalition is likely to fall apart in the long term. This issue is investigated elaborately in chapter 3.

A frequently used term in the field of horizontal logistics cooperation is *flexibility*. In this dissertation, flexibility is defined as *the degree to which companies are willing to adapt themselves to accommodate a more efficient logistics planning for the coalition as a whole*. Flexibility therefore implies that a partner allows a shift in decision-making by giving more degrees of freedom to the coalition when looking for an optimal logistics planning. Examples of flexibility include changing (or postponing) a delivery date, accepting a time window violation and not prioritising its own customers.

2.3 Current research agenda

Horizontal cooperation is a rather recent research topic in the field of operations research and logistics optimisation. Although the available literature is still limited, the topic is gaining momentum and receives increasing interest from both researchers and practitioners. This section summarises the current research agenda and state of the art on HLC for each level of decision making: strategic, tactical and operational.

The aim of this section is not to provide a detailed literature review but to give the interested reader a general overview of existing research directions in horizontal cooperation. For a more elaborate overview of the literature, we refer to Amer and Eltawil (2015) and Verdonck et al. (2013).

2.3.1 *Strategic level*

Setting up a HLC requires a long-term commitment from all companies involved. The success of the collaboration is largely determined by the formation and design of the supply chain network and the selection of the right partner(s) is crucial (Amer and Eltawil 2015). The main research questions at strategic level are:

1. **How to find the best partner(s) to cooperate with?**
   In the academic literature this is referred to as the *strategic fit* (Naesens, Gelders, and Pintelon 2009).
   Related references: Bahinipati, Kanda, and Deshmukh (2009), Feng, Fan, and Ma (2010), Kayikci and Stix (2014), and Naesens, Gelders, and Pintelon (2009)

2. **What is the intensity of the collaboration?**
   To what extent are the partners sharing information and integrating their decision making process? Based on the level of integration multiple types of horizontal cooperation are defined in Cruijssen, Dullaert, and Fleuren (2007). These types range from mutually recognised partners that, to a limited extent, coordinate their activities and planning, to participants that integrate their operations to a significant level where each company regards the other(s) as an extension of itself.
   Related references: Audy et al. (2012) and Daudi, Hauge, and Thoben (2016)

3. **Which supply chain network design is considered appropriate?**
   What is the most optimal supply chain configuration for the coalition of partners such that the required transportation requests can be executed in an efficient way. The opening of shared warehouses, consolidation centres or other facilities and total network optimisation are the main issues in the research field.
   Related references: Ballot and Fontane (2010), Groothedde, Ruijgrok, and Tavasszy (2005), Liu, Zhou, and Zhang (2010), Pan, Ballot, and Fontane (2013), and Pan et al. (2014)

2.3.2 *Tactical level*

The decisions made at the tactical level typically consider a medium-long term planning horizon. We assume the coalition to be formed and aim at providing a framework that can support the daily (operational) decision-making processes.

1. **How to select an appropriate cost allocation (or gain sharing) mechanism?**
   The costs generated by the coalition of collaborating partners and the profits obtained as a result of the cooperation should be allocated back to the individual partners. As this issue will play a major role in this thesis, it is introduced elaborately in chapter 3.

2. **What are the medium-long term KPIs?**
   The success of the cooperation is likely to be evaluated based on its performance on a set of predefined KPIs. The selection of these criteria is directly linked to the main targets and goals of the collaboration in the medium-long term. Part iii of this thesis is devoted entirely to the inclusion of objectives at both the level of the coalition and the level of the individual partners in the operational optimisation procedures.

2.3.3 *Operational level*

At the operational level, collaborating companies allocate inventory/production capacity to order and schedule truckload movements of multiple shippers (Amer and Eltawil 2015). Two main approaches can be distinguished: order sharing and capacity sharing (Verdonck et al. 2013).

1. **How to optimally re-allocate orders (transportation requests) to collaborating partners?**
The majority of all contributions to operational optimisation in HLC consider a *joint route planning* approach, in which customer orders from all participating carriers are combined and collected in a central pool and efficient route schemes are set up for all requests simultaneously using appropriate vehicle routing techniques. Such a centralised approach, in which all partners reveal their transportation requests to the others, is also adopted in this dissertation. Alternatively, also decentralised approaches are gaining ground, as they require partners to reveal only a subset of their orders. These decentralised approaches include for example *auction-based systems* (Dai and Chen 2011) in which partners can bid on orders or transportation requests pooled by the other coalition members. In this case, the operational planning is performed by each partner individually for which traditional, non-collaborative techniques can be used.
Related references: Cruijssen et al. (2007), Hernández and Peeta (2011), Li, Chen, and Prins (2016), Verdonck et al. (2013), and Wang and Kopfer (2014)

2. **How can available capacities be exchanged among different partners?**
Instead of exchanging transportation requests, companies can decide to share resources (vehicles, warehouses, ...) to split large capital investments or risks.
Related references: Yu, Benjaafar, and Gerchak (2015)

3. **How to construct an optimal logistics planning for the group of collaborating companies**
The allocation of customers to vehicle routes, and determining an optimal customer sequence for each vehicle is the main focus of the vast literature on the vehicle routing problem. However, the question is whether and how these approaches, developed for solving non-collaborative problems, can be used to tackle logistics optimisation problems in the context of horizontal cooperation. This is the main focus of part iii of this thesis.

As the main focus of part iii of this thesis is on the operational optimisation of a HLC, a more elaborate literature review can be found at the beginning of chapter 6.

Furthermore, it is likely that decision made at a certain level will impact the decision-making process at the other levels. Some researchers focus on the interactions between different levels of decision making. For example, Cruijssen et al. (2007) and

Palhazi Cuervo, Vanovermeire, and Sörensen (2016) study the impact of operational characteristics on partner selection. Especially in part ii of this thesis, we will focus on the interaction between the tactical and operational level.

3

Gain sharing and cost allocation

3.1 The need for cost allocation (or gain sharing)

In a classic, non-collaborative scenario it is straightforward that each company is responsible for all costs related to its own logistics activities. In general, optimisation methods are therefore designed to minimise the total cost or distance driven by the vehicles. Contrary to this approach, in a cooperative environment multiple companies are jointly optimising their logistics activities. As a result, the costs and profits generated are shared by all member of the coalition. To properly divide these costs or profits among the collaborating partners, a gain sharing (or cost allocation) method to be selected. A large part of the literature on HLC is therefore devoted to profit (or cost) allocation methods. We refer to Guajardo and Rönnqvist (2016), Kimms and Kozeletskyi (2016b), and Lozano et al. (2013). Next to finding the right partners, ensuring a fair allocation of the costs and benefits to all partners is considered one of the main challenges in the context of horizontal cooperation (Cruijssen, Cools, and Dullaert 2007).

When costs and gains are generated as a result of a cooperation between different partners, it is not trivial to determine which partner has a right to which fraction of these gains and which partner should pay what part of the coalition cost. In the current literature, the focus lies on the concept of *fairness* by questioning which allocation is fair for every partner in the coalition. Different definitions of the fairness criteria have resulted in a large set of *cost allocation methods* going from straightforward rules of thumb to more complicated concepts described in the game theory literature. Rather than dividing the coalition cost between the partners, the coalition can also agree to share the total gain. In this case, a *gain sharing method* — also called *profit allocation methods* — is used. Although all cost allocation methods can also be used to allocate the profit, the result for each partner is generally not the same, and the decision to allocate the coalition gain or the coalition cost should be taken with caution. In the remaining part of this chapter, we will focus on cost allocation.

3.2 The principles of cooperative game theory

Cooperative game theory is the field of research that studies the strategic interactions between multiple agents (referred to as *players*). The essence of cooperative games is that players are supposed to be rational and able to design and implement strategies leading to a Pareto improvement as compared to the outcome of the purely noncooperative version of the same game (Lambertini 2011). In other words, cooperative game theory is about how to create benefits for the group, rather than focusing solely on your personal profit, and how to divide/share these benefits among all players (Shubik 1984).

In the context of horizontal cooperation, the engagement of a group of collaborating partners (the grand coalition) to exchange transportation requests and jointly optimise their logistics activities can be seen as the cooperative game. For this grand coalition or any possible subcoalition S, the cost of the joint planning $c(S)$ is usually represented by the total transportation cost. The aim is then to divide the total transportation cost among the individual partners. In what follows, let Ψ be the set of all possible outcomes ψ of the cooperative game and ψ_i the cost allocated to partner i.

3.2.1 *The characteristic function*

Besides the set of players, a cooperative game consists of a *characteristic function*. This function, denoted by c, associates a number $c(S)$ with every subset $S \subseteq N$, which can be interpreted as the cost incured when the members of S cooperate with each other. In sum, a cooperative game is a pair (N, c), where N is a finite set representing the grand coalition and c is a function mapping subsets of N to numbers (Brandenburger 2007).

3.2.2 *The core*

A central concept in cooperative game theory is the *core*. The core of the game is the set of all stable cost allocation results. This implies that for all cost allocation results in the core, there is no subset S such that its players would get a better outcome by deviating from the grand coalition (Guajardo and Rönnqvist 2016). The core can be represented as follows:

$$core = \{\Psi | \sum_{i \in N} \psi_i = c(N), \sum_{i \in S} \psi_i \leq c(S) \;\; \forall S \in N\} \tag{3.1}$$

3.3 Methods for cost allocation

From the numerous cost allocation methods available in the literature, we selected the most important and commonly used ones. The **Shapley value** and **Nucleolus** are both based on the fundamentals of cooperative game theory, whereas the **Equal profit method**, the **Alternative Cost Avoided Method** and the **Volume-based allocation** can be considered more intuitive rules of thumb.

3.3.1 *The Shapley value*

Consider the formation of the grand coalition to be a sequential process, where the partners enter one by one (Tijs and Driessen 1986). Each time a new partner joins its predecessors, the total coalition cost is likely to increase. By repeating this for any possible permutation of the order of entering and averaging the obtained marginal profits in a uniform manner, the *Shapley value cost allocation method* is obtained. This method is based on the *Shapley value*, introduced by Nobel Prize winner Shapley (1953).

Because the Shapley value takes into account the marginal effect of a partner on *all (sub)coalitions* it is said to be based entirely on a partner's *cooperative productivity*. The portion of the cost assigned to partner i is given by the following formula:

$$\psi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!(|N| - |S| - 1)!}{|N|!} (c(S \cup i) - c(S)) \tag{3.2}$$

Using the Shapley value as an allocation method is increasingly popular, in part because it has been put forward by the European CO^3-project. Nevertheless, the CO^3-consortium also acknowledges the need to select a gain or cost allocation mechanism on a case-by-case basis (Biermasz 2012).

Its drawback, however, is the need of information. The calculation of the Shapley value requires at least an estimation of the total cost or benefit of every possible subcoalition. In other words, the full characteristic function of the game should be known. As there is no information available on the decision making and partner behaviour in all unformed coalitions, this might turn out very challenging or even impossible in practice.

3.3.2 *The nucleolus*

The Nucleolus, as defined by Schmeidler (1969), is an allocation mechanism based on the idea of *minimizing the maximum 'unhappiness'* of each individual partner. In this context, unhappiness is measured by the *excess* of the proposed allocation, defined as:

$$e(\psi, S) = \sum_{i \in S} \psi_i - c(S) \tag{3.3}$$

The excess can be interpreted as the gain that the partners in a subcoalition S would obtain if they withdraw from the grand coalition N. It can thus be seen as an incentive for these partners to leave the grand coalition. By minimising this incentive, the stability of the grand coalition can be maximised.

To evaluate different allocations based on the excess, a sequence of linear programs (LPs) should be solved. For increasing coalition sizes, these LPs increase in complexity and computation time, making the interpretation and applicability of the Nucleolus in industry almost impossible. Nevertheless, a unique and stable solution is guaranteed in the centre of the core.

3.3.3 *The equal profit method*

A more intuitive way of dividing the coalition cost among all collaborating partners is presented by Frisk et al. (2010). Based on the idea of obtaining relative savings as equal as possible for the partners, he proposed the Equal Profit Method (EPM). The calculations can be done by solving a straightforward linear program that minimises the largest relative savings difference between any pair of partners. By doing so, a stable solution is guaranteed. Therefore, the EPM can only be calculated if the core is non-empty.

It can be argued that it might seem fair to offer the same relative savings to every partner in the coalition. However, the profit allocated to each partner strongly depends on its stand-alone cost. As a result, companies with a higher stand-alone cost (which might be due to operational inefficiencies) will receive a larger absolute part of the coalition gain when the method is used for gain sharing.

3.3.4 *The alternative cost avoided method*

A sub-category of allocation methods is based on the principle of first dividing the total coalition gain in a *separable* and a *non-separable part* (Tijs and Driessen 1986).

As discussed by Tijs and Driessen (1986), a sub-group of allocation methods is based on the principle of first dividing the total coalition cost in a *separable* (m_i) and a *non-separable part* ($c(N) - \sum_j m_j$). The first part, linked to one specific partner, is defined as the *marginal cost when that partner enters the coalition consisting of all other partners* (Vanovermeire, Vercruysse, and Sörensen 2014). The remaining, non-separable, part can then be divided in various ways. Based on the individual contributions of each partner, the *alternative cost avoided method* (ACAM) defines a set of weights that can be used to divide of the non-separable costs. These weights are based on the differences between the stand-alone cost and the marginal cost of a partner. The part of the total coalition cost allocated to partner i, is thus:

$$\psi_i = m_i + (c(N) - \sum_j m_j) \frac{c(i) - m_i}{\sum_j (c(j) - m_j)} \tag{3.4}$$

3.3.5 *Volume-based allocation*

In practice, companies mostly stick to the more straightforward allocation methods that can be easily interpreted and offer a certain transparency (Frisk et al. 2010). For these *proportional allocation methods* the total coalition costs is divided by calculating a weight for each partner. When a volume-based allocation is used these weights are based on the volume, e.g. the number of pallets, the total weight, ..., shipped by that partner with respect to the total coalition volume.

$$w_i = \frac{volume_i}{\sum_i volume_i} \tag{3.5}$$

3.4 **Properties of cost allocation**

In order to evaluate an allocation mechanism, the field of cooperative game theory provides a number of properties that are considered important (Tijs and Driessen

1986) in order to guarantee *fairness* of the results. We summarise the most important ones.

First of all, the allocation needs to be *efficient*, which means that exactly the entire cost (or profit) should be divided among the partners.

The property of *individual rationality* ensures that the situation of a partner does not worsen by joining the coalition. In other words, when applying a profit allocation method, each partner should be assigned a positive profit. If this property is not realized, the global coalition will tend to break up, as the affected partner will have an incentive to leave. If the allocation method ensures individual rationality for every sub-coalition, the result is said to be *stable*. So, when choosing a stable allocation method, none of the partners can improve their situation by leaving the grand coalition to form a sub-coalition. The solution set of all possible stable cost (or profit) allocations is represented by the *core*.

The *additivity* property ensures that the allocation cannot be influenced by making larger coalitions in advance. The cost, allocated to company i and j, should therefore be equal to the cost a company would have to pay that represents $i + j$.

The *dummy player* property states that a partner that neither helps nor harms any (sub)coalition is allocated a zero-profit or a cost equal to its stand-alone cost.

Lastly, *symmetry* means that partners that are identical (generate the same cost in each coalition), should be allocated the same cost.

Multiple allocation methods have been proposed and developed that each possess a subset of the most desired properties. A single method that has all properties does not (yet) exist. Table 3.1 shows the properties of each of the cost allocation methods described in this section.

3.5 **Individual rationality**

3.5.1 *The limits of flexibility*

By applying a weighted cost allocation method like the Alternative Cost Avoided Method (ACAM) or volume-based method, a cost is assigned to a partner ranging

Table 3.1: Properties of the different allocation mechanisms.

	Shapley	**Nucleolus**	**ACAM**	**EPM**	**Volume**
Efficiency	✓	✓	✓	✓	✓
Individual rationality	✓	✓	✓	-	-
Stability	-	✓	-	-	-
Additivity	✓	-	-	-	-
Dummy player property	✓	✓	-	-	-
Symmetry	✓	✓	✓	✓	-

from zero — where the partner does not pay anything — up to the total coalition cost. This may in some cases result in an allocation that is not individually rational, i.e., in which one or more partners are assigned a larger cost than their stand-alone cost. Such allocations will generally result in infeasible solutions, as the affected partners will not accept to be charged a larger cost than their stand-alone cost, and will consequently leave the coalition.

Let Ψ be the set of all possible cost allocations. We further define $\Psi_{IR} \subseteq \Psi$ as the subset of all individually rational cost allocations. The existence and size of the subset of individually rational allocations depend on the partners' stand-alone cost. In other words, the region of individual rationality of a cost allocation is bounded by the stand-alone costs.

For a two-partner coalition, the concept of individual rationality is visualised in fig. 3.1. The range of possible allocations is represented by segment $\alpha\delta$. However, only solutions between β and γ, calculated based on the partners' stand-alone costs, possess the property of individual rationality. In order to ensure that the collaboration remains beneficial for all partners, only solutions within the set of individually rational allocations should be considered.

Depending on the stand-alone cost of partner 1, the incentive for partner 2 to behave in a more flexible way is bounded. The fact that partner 1 is not willing to pay a cost that is larger than its own stand-alone cost, and that the total coalition cost needs to be paid by the two partners, determines the minimum cost that partner 2 needs to pay. The maximum flexibility of this partner is therefore limited. Consider to following example. As partner 2 behaves more flexible, the cost allocation result is expected to shift towards γ, as we would like to encourage the flexible behaviour.

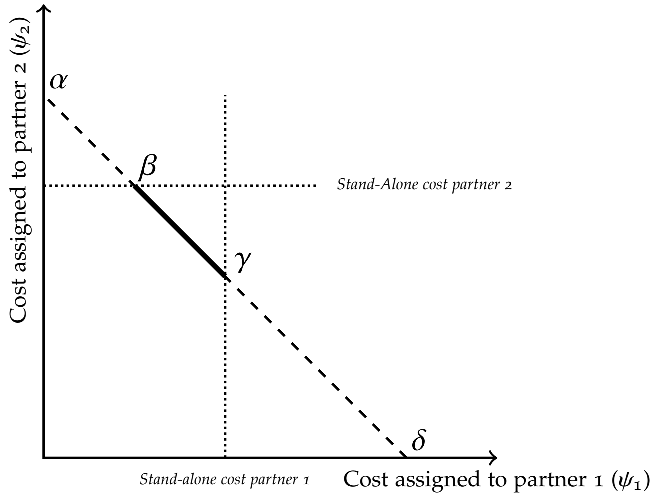


Figure 3.1: Visualisation of the bounded individual rationality for a two-partner coalition.

However, from the moment this corner point is reached, an additional increase in flexibility will no longer result in a cost reduction for partner 2 as this would lead to a violation of the individual rationality constraint.

Clearly, these arguments are symmetrical and we can therefore state that the incentive towards flexibility is *bounded by the stand-alone costs of the coalition partners*. This result also acknowledges the importance of *partner choice* when setting up a new collaboration.

3.5.2 *Towards an individually rational cost allocation*

By using a weighted allocation mechanism, the total coalition cost might be allocated in a way that is not individually rational. In this section, we therefore develop an algorithm that transforms an allocation that is not individually rational into one that is, while remaining as close as possible to the original allocation. For a cost allocation $\psi \notin \Psi_{IR}$, a transformation is proposed towards a new cost allocation $\psi^R \in \Psi_{IR}$ in such a way that the distance between ψ and ψ^R is minimised. We therefore define the *distance between two allocations*, ψ and ψ^R, as the sum over all partners of the squared differences. As these sum should be minimised, allocation ψ^R can be found as follows:

$$\psi^R = \arg\min_{\psi^R \in \Psi} \left(\sum_{i=1}^{N} (\psi_i - \psi_i^R)^2 \right) \tag{3.6}$$

Subject to

$$\psi^R \in \Psi_{IR} \tag{3.7}$$

In order to transform any cost allocation into an individually rational one, we propose the following algorithm. The algorithm makes use of the *cost excess* e_i, defined as the difference between the currently allocated cost and the stand-alone cost of partner i.

$$e_i = \psi_i - c(i) \tag{3.8}$$

If this excess is positive, the allocated cost exceeds the stand-alone cost and the solution is not individual rational for partner i. As a result, partner i will not be willing to participate in the coalition.

The proposed algorithm is based on an iterative search where the largest positive excess is reduced until it equals the stand-alone cost of the corresponding partner and, as a consequence, individual rationality is reached for that partner. The excess cost that is to be paid, is divided equally among the remaining partners. As no extra cost can be allocated to partner i, this partner is removed from the list. This procedure is repeated until the complete solution has reached individual rationality. In this way, a partner will never be charged a cost that is larger than its own stand-alone cost while preserving the initial incentives of the chosen allocation mechanism as much as possible.

The procedure assumes that the total coalition cost is lower than the sum of stand-alone costs of all partners involved. In other words, we assume the property of *superadditivity*. If this condition is not met, it will be impossible to obtain an individual rational solution. Even with all partners paying a cost equal to their stand-alone cost, a part of the total coalition cost will remain unpaid.

Algorithm 1 Pseudocode for transforming a cost allocation result towards individual rationality while preserving the original incentives as much as possible

$|N|$ = number of partners in the grand coalition
$c(i)$ = stand-alone cost of partner i
ψ_i = current cost allocated to partner i
e_i = cost excess of partner i given the current allocation
i, p = partner indices
Require: $\sum_i c(i) \geq \sum_i \psi_i$
while $|N| > 0$ **do**
    $e_i = \max_{k \in \{1,\ldots,|N|\}} e_k$
    if $e_i \leq 0$ **then**
        stable solution found, **end algorithm**
    else
        $\psi_i \leftarrow c(i)$
        for $p \neq i$ **do**
            $\psi_p \leftarrow \psi_p + \frac{e_i}{|N|-1}$
        end for
        remove partner i
        $|N| \leftarrow |N| - 1$
    end if
end while

Although the obtained allocation is now individually rational, it does not guarantee the property of *stability* for the coalition. A coalition is considered stable if none of the partners can improve their situation by forming a sub-coalition. In order to test this, all possible sub-coalitions and their corresponding costs have to be known. However, in real life situations, these costs are generally not known and may be hard to simulate.

Furthermore, although the procedure outlined here finds the individually rational cost allocation closest to the original allocation, the distance between both allocations may be significant. Due to the feedback loop this might lead to a change in strategic positioning that is no longer beneficial for the group as the conversion towards individual rationality can flatten the importance of the initial incentives. As a result, the fact that the coalition divides its costs in a way that is individually rational may not be sufficient to ensure that all partners are comfortable in the created collaborative environment. This has to be evaluated again by every single company in a case-by-case approach.

The proposed transformation is illustrated by a simple example (see also table 3.2). Assume a 4-partner coalition with given stand-alone costs $c(i)$ and a resulting cost allocation ψ_i. As the sum of all stand-alone costs (1400) is larger than the sum of the total coalition cost ($\sum_i \psi_i = 1300$) an individual rational allocation can be found for this coalition. In a first iteration the cost excess e_i is calculated for every partner as the difference between ψ_i and $c(i)$. The largest excess can be found by partner C, and appears to be positive, indicating that the current allocation is not yet individual rational. The cost allocated to partner C is set equal to its stand-alone cost, and the excess of 90 is divided equally among the other partners. As a maximum cost is now allocated to partner C, it is no longer taken into account. Again the cost excess is calculated for every partner, showing still a problem concerning individual rationality for partner A (40). The cost allocated to this partner is therefore set equal to its stand-alone cost, and the excess is again divided among all other partners that are still in the list. By calculating the cost excess one last time, it can be seen that they are all negative and an individual rational cost allocation is obtained.

Table 3.2: Illustrating example of the transformation algorithm.

	partner A	**partner B**	**partner C**	**partner D**
$c(i)$	200	350	500	350
ψ_i	210	290	590	210
e_i	10	-60	**90**	-140
ψ'_i	240	320	500	240
e_i	**40**	-30	//	-110
ψ''_i	200	340	500	260
e_i	//	-10	//	-90

Part II

PROVIDING INCENTIVES THROUGH GAIN SHARING OR COST ALLOCATION

4

Gain sharing and incentives, an empirical approach

Abstract:

More and more companies start to notice the potential of setting up a logistics cooperation. They realize however that this idea is also a source of new challenges and impediments. We will focus on the challenge of dividing the total coalition gain among all partners. In this chapter, we show that significant differences exist between allocation methods and we examine the impact of defining gain sharing on a short term (daily) or a long term (monthly) basis. Too often, the selection of an appropriate allocation mechanism is considered as an independent decision with fairness *as the single criterion. The companies involved, however, should realize what the impact of a certain allocation method might be, when applied in the broader context of horizontal cooperation. A selection of well known allocation methods and concepts is introduced and applied to a real life case study of fresh produce traders, jointly organising their transportation from the auction to a joint transport platform.*

4.1 Introduction and literature review

When gains are generated as a result of cooperation between different partners, it is not trivial to determine which partner has a right to which fraction of these gains. In the current literature, the focus lies on the formulation of the concept of *fairness* by questioning which allocation is *fair* for every partner in the coalition. Different definitions of the fairness criteria have resulted in a large set of *gain sharing methods* — also called *profit allocation methods* — going from straightforward rules of thumb to more complicated concepts described in the game theory literature. Rather than dividing the coalition gain between the partners, the coalition can also agree to share the total cost. In this case, a *cost allocation method* is used. Although all cost allocation methods can also be used to allocate the profit, the result for each partner is generally not the same, and the decision to allocate the coalition gain or the coalition cost should be taken with caution. We refer to chapter 3 for a more elaborate introduction on gain sharing and cost allocation.

In this chapter, a new approach is introduced that can help a coalition in choosing the appropriate allocation mechanism. In stead of focusing on fairness, which remains rather subjective, we argue that gain sharing should be evaluated within the broader idea of horizontal cooperation. As for every gain sharing method certain partner characteristics are favoured, the coalition as a whole implicitly imposes the incentive to the partners to score well on these characteristics. Some coalitions will wish to encourage the partners to take a flexible stance with respect to their delivery terms (e.g. wide time windows, orders that can be delivered on different days), whereas others will prefer partners to ship as much as possible.

This approach is studied on real life data, provided by a coalition of produce traders (see section 4.2). All gain sharing methods introduced in chapter 3 are compared: the **Shapley value**, the **Nucleolus**, the **Equal Profit Method (EPM)** and the **Alternative Cost Avoided Method (ACAM)**. The results of these allocation methods are compared to each other, and to the **Volume-based method**, that is currently used in this particular horizontal cooperation.

4.2 Case study: Cooperation among fresh produce traders

Fresh fruit and vegetables are typically traded at an auction from which they are transported to the customers in temperature-controlled trucks. Fresh produce is highly perishable and an efficient supply chain is of crucial importance to maintain customer service levels.

In 2012, three traders at a Belgian fruit and vegetables auction launched, under the supervision of a neutral third party, a joint shuttle service between the auction and the traders' common transport platform, about 250km to the east. This shuttle service was outsourced to a specialized Logistics Service Provider (LSP).

A twofold, positive effect could be observed. First, the shuttle service guaranteed the traders that their goods, even the ones bought last-minute, can be transported in an appropriate way. A reliable truck, departing no later than 11.00am from the quay at the auction, provided the necessary temperature controlled (8°C) transportation. Furthermore, by combining the orders of the three traders and thereby increasing the transported volume, better prices could be negotiated from the LSP.

A yielding pace list was negotiated that determined the transportation price as a function of the total shipped order size (i.e., the number of pallets). The regressive character of this instrument was meant to stimulate the traders to increase their order quantities. Since the total cost of the shuttle truck is calculated based on the consolidated volume, the traders are pushed to avoid small shipments by buying extra products at the auction or by moving their delivery to the next day, if feasible.

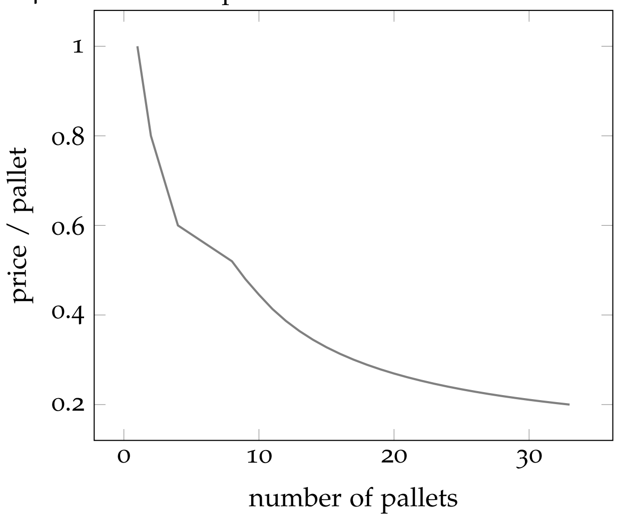
From their side, the auction authorities encourage this horizontal cooperation project in two ways. First, priority is given to the shuttle service by assigning a specific quay to it. Secondly, the auction also acts as a neutral party by keeping track of the consolidation gains (i.e., the profit obtained by switching from individual transport to the shuttle service). Periodically, these gains are divided among the traders, using the Volume method, i.e., proportional to the number of traded pallets.

In this chapter, we scrutinize the way in which the consolidation gains are divided by the agreement between the traders. Next to the current way of working, we examine the properties and results of the gain sharing methods discussed in section 3.3. All calculations are executed by using a spreadsheet (MS Excel 2010 in Windows 7). We find that different gain sharing mechanisms give largely different results, and also result in different *incentives* for the partners in the coalition. For these reasons, we conclude that it is important to select an adequate gain sharing mechanism.

4.3 Simulation results

The shipped volumes of the coalition were observed during a period of eight weeks. The cost of every (sub)coalition is calculated based on the pace list (fig. 4.1), negotiated with the logistics service provider[1]. In case of multiple trucks on one day an optimal load distribution with minimal total costs is assumed. A full truck load consists of 33 pallets.

Figure 4.1: The relative pace list for the traders' shuttle truck.



The parties involved agreed on a volume-based gain sharing method, because of simplicity and transparency reasons. The traders receive a part of the coalition gain according to their individual volumes, calculated by the number of pallets, which gives them the incentive to place larger orders. The profits, held by the auction authorities as a neutral party, are periodically divided among the traders. The logistics service provider is paid according to the consolidated volumes. During the considered period of eight weeks, the total coalition gain reached more than €2000, which corresponds to a global cost reduction of 16%.

In this section, the characteristics of the different partners are introduced (section 4.3.1) and the need for a gain sharing method that produces a stable allocation is discussed (section 4.3.2). The difference between gain sharing on a day-to-day basis or on an aggregated (e.g. weekly) basis is shown in section 4.3.3. Finally, section 4.3.4 handles the difference between the original rigid scenario and a flexible scenario

1 The pace list is anonymised by normalising it between 0 and 1

where partners accept that small orders are stored at the auction and delivered the next morning in order to avoid the higher price per pallet for small order sizes.

4.3.1 *Characteristics of the partners*

The shuttle truck service is shared by three partners (A, B and C). The first partner (A) transports high volumes (61% of the total volume of the coalition) and nearly every day. Therefore, this partners requires a Full Truckloads (FTLs) on a regular basis. As no bundling is possible with these shipments, FTLs are not beneficial for the total coalition.

Partner B also makes use of the shuttle truck on a very regular basis, but with lower average order sizes. In the stand-alone scenario, this will result in a higher cost per pallet. By combining the orders with other partners, significant synergies can be expected. Because orders of partner B are less-than-truckload, they can be combined more easily with other less-than-truckload orders.

Lastly, the third partner (C) also places small orders that can be combined easily with other partners. However, the degree of participation is rather low for this partner (only 9% of the total volume, and 30% of the movements) reducing again his impact on the synergy of the total coalition.

4.3.2 *Stability*

When setting up a new coalition, the potential partners need to take into account the stability of the grand coalition. If a subcoalition exists that is in any way more beneficial for one collaborating partner, than the long–term stability of the grand coalition can no longer be guaranteed. Stability is ensured in two ways.

Firstly, the gain of a subcoalition may never exceed the total coalition gain. If this is the case, a better performing subcoalition could be formed by leaving out some partners. This is known as the problem of *strong subcoalitions* (Vanovermeire, Vercruysse, and Sörensen 2014). For the shuttle truck case, studied in this chapter, it can be seen in table 4.1 that the total cost of a (sub)coalition is always smaller than the summed stand-alone costs of the partners involved. Additionally it is clear that by forming the grand coalition (A-B-C) the highest gains are obtained. Despite the stability of the aggregate data, it remains possible that on a daily basis non-stable collaborations existed. In the sample studied in this chapter, one observation involved a strong subcoalition. On this day, a cooperation with only two partners would generate a higher profit, compared to the current situation that includes all three partners. This possible short-term instability does not necessary endanger the long-term stability of the total coalition and is rather rare and temporary. However, it causes an infeasible solution for the equal profit allocation method for this one day.

Table 4.1: Aggregated total cost of the (sub)coalitions for the shuttle truck case study.

Subcoalitions		**A**	**B**	**C**	**A–B**	**B–C**	**A–C**	**A–B–C**
Original	cost	€6142	€4844	€1646	€9847	€5733	€7441	€10564
	profit				€1138	€757	€347	€2068
Flexible	cost	€6096	€4680	€1475	€9548	€5400	€7038	€10110
	profit				€1229	€756	€534	€2142

Secondly, the allocation mechanisms need to ensure that the costs paid by the different partners in the grand coalition are always lower than the corresponding stand-alone costs. In section 3.4 this idea was introduced as the property of individual rationality. If this property is not fulfilled, a partner may not want to collaborate and the grand coalition may split up.

In table 3.1 in section 3.4 it can be seen that only one of the five allocation methods proposed in this chapter, the Nucleolus, guarantees a stable solution. Even the less restrictive property of individual rationality is not guaranteed in some of the methods. However, it might be useful to remark that, although it is not guaranteed mathematically, all results obtained for this case study are individual rational — no partner is allocated a negative profit — and stable — except for one day, as described above.

4.3.3 *Aggregation of profit allocation*

Depending on the allocation method, a different division of the profits is realized when the allocation takes place on a daily basis or on aggregate level (e.g. weekly or monthly). These differences between the allocation methods are demonstrated in table 4.2a.

For the Shapley value, the Nucleolus and ACAM, similar results are reported in the rigid planning method on a daily basis. This is due to the fact that most of the time only two partners use the shuttle truck on the same day. In a coalition with only two partners, these three allocation methods split the profit in two equal parts. The volume-based allocation and the equal profit method however differ, allocating less to the smaller partners, B and C, in favour of partner A.

Significant differences are found comparing daily allocation with respect to aggregated allocation. At the aggregate level, the gains are divided among the three partners based on their total contribution during the period. Due to the aggregation, the multiple two–party cooperations that are observed will be summed and the Shapley Value, Nucleolus and ACAM no longer divide the gains equally among the partners. Here, the Nucleolus tends to allocate more to partner A, due to his higher stand-alone cost and the property of finding a solution in the centre of the core.

It can be argued that a daily allocation gives a better approximation of the real costs and profits per partner. Aggregating costs flattens the real costs of single transports, which is thus taken less into account when calculating the profit allocation. The differences between daily and aggregated allocation can be up to 46%.

Exceptionally, the Shapley value, because of the property of additivity that this method possesses and the fact that it is fully based on efficiency of the transportation, is insensitive to the level of aggregation.

4.3.4 *Flexibility to support the coalition*

The price that is to be paid by the traders for the transport depends on the shipped volume according to a negotiated pace list, which makes smaller shipments rather costly. To avoid high transportation costs, the coalition has agreed to strive towards shipments of at least ten pallets. If this threshold is not reached the traders are motivated to buy extra products or to delay the delivery by one day if possible.

In our simulations, two alternative scenarios are considered. In the *rigid* scenario (see table 4.3a) all orders are shipped on the day they are placed, which is the current situation. The *flexible* scenario (see table 4.3b) assumes that small order sizes (less than 10 pallets) can be stored at the auction for one day and combined in the next day truck if this yields a smaller total cost.

Table 4.2: Allocation of coalition gain by the different methods. For the aggregated allocation we assume that the cost allocation was only done at the end of the eight-week sample.

(a) rigid planning *(total profit = €2068)*

	Daily allocation			Aggregated allocation		
	A	B	C	A	B	C
Volume	€1034	€673	€361	€1264	€611	€193
Shapley	€684	€891	€494	€684	€890	€494
Nucleolus	€684	€976	€409	€846	€757	€464
ACAM	€685	€893	€495	€684	€898	€485
EPM	€866	€792	€411	€1005	€793	€269

(b) flexible planning *(total profit = €2142)*

	Daily allocation			Aggregated allocation		
	A	B	C	A	B	C
Volume	€1097	€692	€353	€1309	€632	€200
Shapley	€756	€868	€520	€756	€867	€519
Nucleolus	€731	€953	€459	€930	€756	€457
ACAM	€734	€851	€559	€741	€876	€498
EPM	€909	€746	€387	€1050	€810	€255

Table 4.3: One-week sample of shipped volumes per partner and for the grand coalition.

(a) rigid scenario

	A	**B**	**C**	**Grand coalition (A+B+C)**	
	volume	volume	volume	volume	coalition cost
day 1	3×33	10		$3 \times 33 + 10$	€1212.70
day 2		5	4	9	€219
day 3	13	22		$33 + 2$	€410
day 4					
day 5	11	10	10	31	€320.54
aggregated	**123**	**47**	**14**	**184**	**€2159.24**

(b) flexible scenario

	A	**B**	**C**	**Grand coalition (A+B+C)**	
	volume	volume	volume	volume	coalition cost
day 1	3×33	10		$3 \times 33 + 10$	€1212.7
day 2					
day 3	13	$22 + 5$	4	$33 + 11$	€557.37
day 4					
day 5	11	10	10	31	€320.54
aggregated	**123**	**47**	**14**	**184**	**€2090.61**

In reality, during the eight weeks of observation, postponement of the transport occurred only once. Therefore, it is simulated that orders of less than ten pallets are automatically moved to the next day, increasing the possibilities of combining orders. table 4.3b contains an example of this practice. As the small volume that is to be shipped on day 2 is relatively expensive, the flexible scenario imposes that these pallets stay at the auction for one more day and are shipped the next morning. Although the total cost of the coalition is lower when flexibility is enforced, the coalition gain might decrease. This is due the fact that the stand-alone cost of the partners also decreases when flexibility is enforced. Nevertheless, because of the lower total coalition cost, the flexible approach will still be beneficial for the coalition.

According to table 4.1, a flexible approach to the entire eight-week data set, increases the coalition gain with €74 (€2142 – €2068). An additional decrease in total coalition cost of around 4.3% can be witnessed by imposing the flexible strategy in stead of the original scenario. This implies that on 12.5% of the reported days, the orders of that day remain at the auction.

The allocated profits for the flexible scenario are shown in table 4.2b. Depending on the chosen allocation mechanism, this flexible strategy turns out to be not that profitable for every partner in the shuttle truck case study. Most of the time, the flexible strategy is less beneficial for partner B.

As the order sizes of B are rather small, a flexible behaviour of B will in the place result in an improved stand-alone position. For partners A and C, this flexibility will affect their stand-alone position less. For partner A, this is due to the fact that its volumes are already large most of the times, so they are shipped anyway. Partner C is not shipping regularly, so leaving its orders at the auction will not lead to any improvement as the probability that this partner will ship again the next day is low. We can therefore state that for partners A and C, only benefits are created when the cooperation is set up. This positive effect on the coalition is captured by the Shapley Value, Nucleolus and ACAM. For the Volume and the Equal profit method, the shipping day is not important and the gains are allocated pro rata. The drop in allocated gain for partner C for the EPM in the different scenario is only due to the on day of strong subcoalitions, for which no EPM can be calculated, as explained in section 4.3.2.

4.4 A different allocation method, a different incentive

Every gain sharing method takes as an input a limited number of parameters and partner characteristics to obtain the final profit that is allocated to every partner. In the previous chapter it could be seen that the Shapley value method is based only on costs, where the volume-based method does only take the shipped volume into account. Similar to the Shapley value, the ACAM is also based on costs but it does not include all possible subcoalitions. This can also be said for the Nucleolus, but from a completely different perspective. The EPM is not based on absolute costs or profits, but divides the gains based on their relative differences. We can therefore state that by choosing a gain sharing method, a certain incentive is given to the partners in the coalition. Because if they are able to improve on the characteristics that are taken into account by the allocation method, a higher gain is allocated to this partner. This idea is summarised in table 4.4.

If the volume-based allocation is chosen, the partners shipping the highest volumes are favoured although their shipments might not be that efficient for the coalition. This method therefore gives an incentive to grow. The ACAM produces similar results compared to the Shapley value. This last one puts a lot of stress on efficiency by taking into account the marginal cost of the different partners in *every* (sub)coalition. Here, the efficiency of a single partner (e.g. the partner is participating a lot and the order sizes leave enough room for combining with others) is rewarded. The Nucleolus refers to long term stability because a solution in the centre of the core is guaranteed. Therefore, no partner feels the incentive to abandon the grand coalition. By stabilizing as much as possible the situation as it is, it will give no incentive to the partners to adapt their behaviour. We therefore state that the Nucleolus gives an incentive of stability to the partners. In contrast to the Shapley Value and the ACAM, the Nucleolus is less steadfast when gains are divided periodically. In both the rigid and the flexible scenario, we observe a significant divergence on the aggregate level where the method is less sensitive for day to day efficiency of the transport. Lastly, the EPM can only be calculated if the coalition is stable. Although we find that for this case study the coalition remains stable in the long run, the stability can not be guaranteed every single day. It can also be seen that, because of the fact the EPM uses relative savings, partners with a high total stand-alone cost, that are therefore inefficient, are favoured at the expense of the efficient ones. It can be argued that this might result in an unfair allocation if the partners differ significantly.

Table 4.4: The incentives of different gain sharing methods.

Allocation method	Partner characteristics	Incentive
Shapley value	stand-alone cost cost of all subcoalitions	partner efficiency
Nucleolus	stand-alone cost cost of all subcoalitions	stability
Equal profit method	stand-alone cost	stand-alone inefficiency
Alternative cost avoided method	stand-alone cost cost of subcoalitions with $\|N\| - 1$ partners	coalition efficiency
volume-based allocation	volume	ship large volumes

4.5 Conclusions and future research

In this chapter, the effect of the selected gain sharing method in a horizontal cooperation is examined by using an empirical approach. For the simulation, we selected five well known allocation methods and applied them on real life data, obtained from a coalition of fresh produce traders. By joining forces, the partners were able to reduce the total transportation cost by 16%.

Firstly, we can conclude that significant differences might exist if the gain sharing is done on a short or a long term basis. This is due to the fact that in the long term the efficiency of individual transportations average out and the results are based on the average performance of the coalition. We recommend an allocation of the gains on the short term, as here the efficiency of the individual transportations is used, resulting in a more adequate approximation of the real costs. One exception here is the Shapley Value, that is not influenced by the problem of aggregation.

In stead of focussing on the concept of fairness, the coalition should be aware of the impact of an allocation method on the more global idea of horizontal cooperation. As every allocation method is based on certain partner and coalition characteristics, incentives are given when selecting a certain mechanism. It can be seen that a Volume-based allocation favours the growth of the partners, without questioning flexibility of the partners or efficiency of the transport. The Shapley value and ACAM on the other hand strive toward efficiency by means of marginal costs. In order to achieve stability, the parties can choose for the Nucleolus as it assures a solution in the centre of the core. However, no direct link to operational parameters or partner characteristics can be found. Therefore, the results might be hard to interpret. Finally, the fairness of the EPM can be questioned in heterogeneous cooperations.

This study also confirms that a more flexible attitude of the collaborating parties results in higher possible profits for the entire group. Still, it remains important to weigh the extra profits against the engagement of being flexible.

This specific cooperation between fresh produce traders is perceived as a success story for both the traders and the LSP. Due to bundling the traders were able to reduce transportation costs significantly. The LSP on the other hand can use his vehicle capacity more efficiently.

The current literature on horizontal cooperation is rather scarce and remains on the surface. For further research, we believe that it might be useful to study in more detail the interactive relationship between the partners behaviour, the operational solution at the level of the coalition and the gain sharing (or cost allocation) mechanism. The Venlo traders case study shows clearly that a flexible behaviour of the partners — allow a shift of one day in the transportation date — can result in a positive cost effect for the coalition. This flexible behaviour should therefore be encouraged by giving the right specific incentives by means of a well-chosen gain sharing or cost allocation mechanism.

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5

Partner behaviour, operational optimisation and cost allocation

Abstract:

This chapter investigates the effect on the cost allocation of a partner's strategic behaviour and the properties of its customer locations (distance to the depot, degree of clustering). Furthermore, we investigate the effect of the cost allocation method used by the coalition.
We consider a selective vehicle routing problem, in which customers belonging to different partners in a logistics coalition are served in a single logistics operation with multiple vehicles. Each partner determines a non-delivery penalty (given by the compensation for non-delivery (CND)) for each of its customers, and a central algorithm creates an operational plan, including the decision on which customers to serve and in which trip. The total transportation cost of the coalition is then divided back to the partners through a cost allocation mechanism.
The well-known Shapley value cost allocation method is compared to our novel, problem-specific method: the CND-weighted cost allocation method. We prove that an adequate cost allocation method can provide an incentive for each partner to behave in a way that benefits the coalition. Further, we develop a transformation that is able to transform any cost allocation into an individually rational one without losing this incentive.

5.1 Introduction and literature review

In recent years *horizontal collaboration* has become increasingly popular in the road transportation industry. The basic idea underlying this innovative business model is that distribution companies can significantly increase the efficiency of their operations by joining forces and becoming partners in a *horizontal logistics coalition*. Especially by solving a *collaborative vehicle routing problem*, i.e., a vehicle routing problem in which customers that would normally be served by different transportation companies are assigned to shared vehicle routes, less kilometers can be driven with trucks that have a higher average fill rate (European Commission 2011; Initiative and Capgemini 2008).

On the other hand, the added complexity of this novel way of working does not come without its challenges. One of the most important issues that needs to be tackled is that of *cost allocation* (also called *gain sharing*, depending on the perspective). A coalition incurs a single global coalition cost, which must be paid by the individual partners. The coalition must therefore install a method to allocate the total coalition cost to the partners. If a partner perceives its allocated share of the coalition cost to be too large, it might leave the coalition. Notwithstanding its importance, the cost allocation problem has been widely ignored in the literature on collaborative vehicle routing.

In this chapter, we argue that solving a collaborative vehicle routing problem requires a more problem-specific approach, that explicitly takes into account the *interaction* between the vehicle routing problem and the cost allocation method. In Vanovermeire and Sörensen (2014a), an approach is developed that explicitly *integrates* the cost allocation method into the operational planning method, resulting in an optimization problem that looks for the least-cost solution under the constraints that each partner should be adequately rewarded for the changed delivery dates of its customers. Such an approach, however, considerably complicates the optimization problem and is therefore not a viable approach in all situations.

The Shapley value (Shapley 1953), the Nucleolus (Leng and Parlar 2005; Schmeidler 1969), the Equal Profit Method (Frisk et al. 2010) and the volume-based allocation are some of the most well-known allocation methods. Some use a game theoretical approach (e.g., the Shapley value and the Nucleolus), others are based on simpler rules of thumb (e.g., the volume-based allocation and the Equal Profit Method).

As every allocation mechanism is based on a number of partner-specific characteristics (e.g., shipped volume, stand-alone cost, flexibility), choosing an allocation method results in an implicit selection of the desired partner behaviour. As an example, the volume-based allocation method allocates the profit of the coalition based on each partner's shipped volume and therefore implicitly stimulates partners to ship larger volumes. Stated differently, by agreeing on a certain cost allocation method, the partners implicitly or explicitly formulate a number of performance indicators they deem important for the coalition. Partners that behave well according to these predefined characteristics will be favoured by the cost allocation mechanism. This mechanism should therefore be used as an incentive for the partners to behave in favour of the coalition (Defryn, Vanovermeire, and Sörensen 2015). Dudek and Stadtler (2005) state that, by giving the right incentives, a solution can be obtained, that is optimal for the total coalition instead of a solution that is locally optimal for only one or a subset of partners.

There is widespread agreement in the literature that no single cost allocation method works best in all situations. In order to be able to include problem-specific elements into the allocation procedure, many authors therefore acknowledge the need for a case-specific approach (Barbarino et al. 2010; Defryn, Vanovermeire, and Sörensen 2015; Tijs and Driessen 1986; Vanovermeire, Vercruysse, and Sörensen 2014). The current literature, however, neglects the impact of the behaviour of an individual partner on the performance of the coalition. To guide this behaviour in a desirable direction, the coalition should give the right incentives to the partners, which, as mentioned, can be achieved by the appropriate cost allocation mechanism.

In this chapter, we emphasize the *interaction* between these different elements — strategic partner behaviour, operational planning, and cost allocation — when operating in a collaborative environment. We focus on a relatively simple (yet realistic) collaborative variant of a well-known vehicle routing problem, the *selective vehicle routing problem*. This problem is formally described in section 5.2. In section 5.3 it is shown how this problem can be used in a collaborative environment. Here we focus on the issue of incorporating individual partner behaviour and a cost allocation method. By means of simulation, the properties and characteristics of the selective vehicle routing problem in a collaborative environment are analysed in section 5.4. Finally, section 5.5 summarises the main results and gives pointers for future research.

5.2 The selective vehicle routing problem

5.2.1 *Problem definition and mathematical formulation*

In the problem discussed in this chapter, both the number of vehicles and the maximum distance each vehicle can travel, are limited. As a result, only a subset of customers can generally be served. The underlying operational problem is therefore a SVRP. In the vehicle routing literature, problems in which not all customers need to be visited, but a "reward" is gained for each customer visit are usually called *orienteering problems*, see e.g., Archetti, Hertz, and Speranza (2007) and Bouly, Dang, and Moukrim (2010).

A formal description of the SVRP tackled in this chapter is the following. We consider a set of c customers c_i, $i = \{1, \ldots, c\}$, with given coordinates in an euclidean distribution area, and a fixed fleet of vehicles, denoted as K. The cost to travel between customers i and j is represented by the distance d_{ij}. Each vehicle can travel a predefined maximum distance D. Furthermore, a depot is given. Each vehicle starts and ends its distribution tour at this depot.

In the SVRP both the number of vehicles and the maximum distance travelled by each vehicle are limiting resources that may prevent all customers from being visited. A CND is therefore determined for each customer. CND_i is the cost that is to be paid when customer i is not served, and may represent, e.g., a penalty paid to this customer in the form of a discount. We will elaborate on this concept in section 5.3.1.

The aim of the SVRP is to determine a feasible subset of customers to be served, as well as the sequence in which these customers are visited by each vehicle in such a way that the *total distribution cost* is minimised. This cost includes both the total travel cost and the total CND value of all unvisited customers. The SVRP therefore implicitly assumes — without loss of generality — that travel distances and the CND are expressed in the same units.

Formally we can define the SVRP as a mixed-integer programming problem. We use the subtour elimination constraints as defined by Vansteenwegen, Souffriau, and Van Oudheusden (2011). In this representation the position of customer i in the path of vehicle k is given by U_{ik}. Other decision variables are the following:

$$x_{ijk} = \begin{cases} 1 & \textit{if a visit to customer } i \textit{ is followed by a visit to customer } j \textit{ in the tour of vehicle } k \\ 0 & \textit{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1 & \textit{if customer } i \textit{ is served in the solution} \\ 0 & \textit{otherwise} \end{cases}$$

$$\min \left[\sum_{i=0}^{c} \sum_{j=0}^{c} \sum_{\forall k \in K} d_{ij} x_{ijk} + \sum_{i=1}^{c} (1 - y_i) \mathrm{CND}_i \right] \tag{5.1}$$

Subject to

$$\sum_{i=1}^{c} x_{imk} = \sum_{j=1}^{c} x_{mjk} \qquad \forall m = 1 \ldots c, \forall k \in K \tag{5.2}$$

$$\sum_{k=1}^{v} \sum_{i=1}^{c} x_{ijk} = y_j \qquad \forall j = 1 \ldots c \tag{5.3}$$

$$\sum_{i=1}^{c} x_{0ik} = \sum_{j=1}^{c} x_{j0k} = 1 \qquad \forall k \in K \tag{5.4}$$

$$\sum_{i=0}^{c} \sum_{j=0}^{c} d_{ij} x_{ijk} \leq D \qquad \forall k \in K \tag{5.5}$$

$$U_{ik} - U_{jk} \leq (c-1)(1 - x_{ijk}) \qquad \forall i, j = 1 \ldots c, \forall k \in K \tag{5.6}$$

$$1 \leq U_{ik} \leq c \qquad \forall i = 1 \ldots c, \forall k \in K \tag{5.7}$$

$$x_{ijk}, y_i \in \{0, 1\} \tag{5.8}$$

Equation (5.2) ensures the connectivity of the path of a single vehicle, while eq. (5.3) guarantee that every customer is visited at most once in the solution. Equation (5.4) ensure that all vehicles start and end their trip at the depot (vertex 0). The maximal allowed vehicle distance is ensured by eq. (5.5). Equation (5.6) and eq. (5.7) take care of the subtour elimination.

5.2.2 *A simple metaheuristic for the selective vehicle routing problem*

Several algorithms have been proposed in the literature to tackle selective vehicle routing problems or team orienteering problems. The most important contributions are summarised in table 5.1. Because none of these algorithms is publicly available, we develop in this chapter a straightforward randomized, multi-start variable neighbourhood search algorithm. Although we are confident that the solutions found by our algorithm are of high quality, the aim of this chapter is not to develop a state-of-the-art algorithm that can compete with the best ones in the literature. The algorithm is visualised in fig. 5.1. In table 5.2 the algorithm's parameter settings, which were determined in a limited pilot study, are presented.

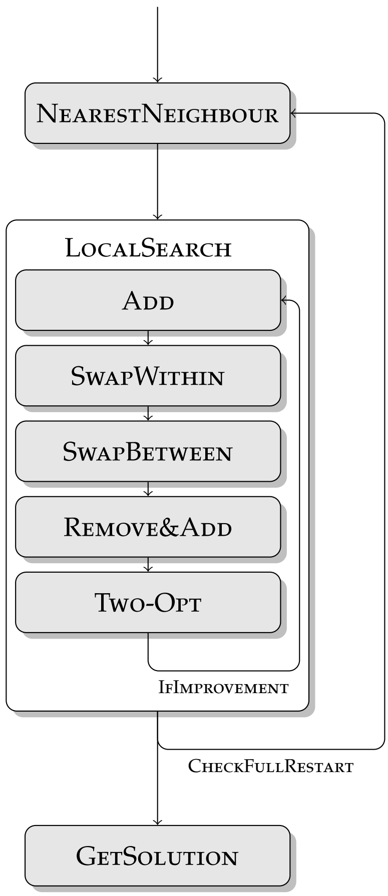


Figure 5.1: Visualisation of the randomized, multi-start variable neighbourhood metaheuristic, used to solve the selective vehicle routing problem.

First a randomized nearest-neighbour heuristic is used to construct an initial solution — where *nearest* is defined as a minimal (distance/CND)-ratio. In this way the solution is constructed by visiting customers that are close to the current position of the vehicle or cause high compensation for non-delivery costs if not visited. Due to this definition, the heuristic automatically ranks customers with zero CND after all

Table 5.1: An overview of the most important contributions to the selective vehicle routing (team orienteering) problem literature from a metaheuristic point of view.

Reference	Algorithm
Tang and Miller-Hooks (2005)	Tabu search
Archetti, Hertz, and Speranza (2007)	Tabu search with penalty strategy Tabu search with feasible strategy Fast variable neighbourhood search Slow variable neighbourhood search
Ke, Archetti, and Feng (2008)	Sequential ant colony optimisation Deterministic concurrent ant colony optimisation Random concurrent ant colony optimisation Simultaneous ant colony optimisation
Vansteenwegen et al. (2009)	Guided local search
Souffriau et al. (2010)	Path relinking
Bouly, Dang, and Moukrim (2010)	Memetic algorithm
Labadie et al. (2012)	Granular variable neighbourhood search

other customers. Obviously, it is not economically meaningful to set a negative CND. Similar to a Greedy Randomized Adaptive Search Procedure (GRASP) algorithm, the constructive algorithm randomly selects one of the NBEST customers at each iteration. This allows it to generate different solutions, which is necessary because of the multi-start nature of the algorithm.

In a second phase the obtained heuristic solution is improved by means of local search, using the different neighbourhoods listed in table 5.3. These neighbourhoods are firmly established in the vehicle routing literature, and are explored sequentially in the order mentioned here. A first-improvement strategy is used, and every improvement encountered is accepted. If none of the neighbourhoods contains a better solution, the current solution is saved as a local optimum.

Table 5.2: Parameters of the randomized, multi-start variable neighbourhood metaheuristic and their values after tuning.

Parameter	Definition	Tuning
NBBEST	Number of best possible next customers that are taken into account for the constructive nearest-neighbour heuristic	4
FULLRESTART	Number of times the full algorithm (construction + local search) is restarted	2000

Table 5.3: The different neighbourhoods explored during the randomized, multi-start variable neighbourhood search.

Neighbourhood	Definition
ADD	Add a customer to the solution if the cost of serving is not larger than the CND and a vehicle is able to fulfil the order without surpassing the allowed distance (denoted as MAXDIST).
SWAPWITHIN	Swap the position of two customers in a single trip.
SWAPBETWEEN	Swap the position of two customers, belonging to different vehicles.
REMOVE&ADD	Remove a customer from the solution and add a new customer if this lowers the total coalition cost.
TWO-OPT	Remove two edges and replace them by two new edges to close the tour, decreasing the total distance, within a single vehicle.

The algorithm is initiated multiple times (FULLRESTART times). The larger the value of this parameter, the larger the possibility to improve the current solution but this comes at the expense of larger calculation times. The solution reported is the best solution found during all iterations of the main loop.

5.3 The SVRP in a collaborative environment

In this section the SVRP is introduced in a collaborative environment in which several companies form a coalition with the aim of serving the customers of all partners in one single logistics operation. By combining their customer bases and sharing their trucks, the individual vehicle routing problems of the partners disappear and a vehicle routing problem arises at the level of the coalition. Increased opportunities for optimisation appear because customers of different companies can be visited by the same truck, which might result in a lower total logistics cost.

Consider for example the case in which multiple providers of heating oil join forces and decide on a joint distribution scheme. By allowing that a customer is served by any of the participating providers, it is likely that more efficient routes can be constructed and, as a result, more customers can be visited in one single day. Customers that ran out of stock should receive a higher priority (especially during cold winter days). Furthermore, these priorities might change over time.

In the rest of this chapter, we consider a grand coalition N, in which $|N|$ partners $p = \{1, \ldots, |N|\}$ join forces. The set of k vehicles is shared and for every customer c_i^p in the grand coalition the partner is indicated by an extra index p. A graphical representation of the selective vehicle routing problem in a collaborative environment can be found in fig. 5.2.

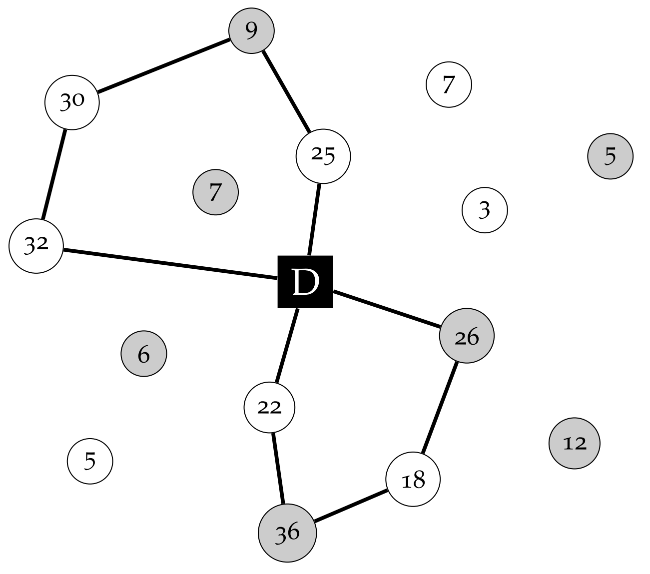


Figure 5.2: The selective vehicle routing problem in a collaborative environment with two collaborating partners (white and gray) and two available trucks.

5.3.1 *Interpretation of the compensation for non-delivery*

A property of the SVRP is that the decision whether to serve a certain customer in the operational plan is not only based on its position in the distribution area but also on its *urgency for delivery*. This urgency is represented by the *compensation for non-delivery cost* (CND), a value that can be determined by each partner individually for each of its customers. The CND of customer i (denoted as CND_i) can be interpreted as a fee that is to be paid if customer i is not served in the solution. It is awarded in order to compensate for the consequences of the postponement of the corresponding order.

In a more concrete example, it can be assumed that partners give a cost reduction to their customers if they are not served on the agreed delivery date. The exact *discount* can be defined by the partner individually and can be interpreted as the CND. Customers that are promised a larger discount, and therefore have a larger compensation for non-delivery cost, are more likely to be part of the optimal solution. The CND values can therefore be used by a partner to prioritize the delivery of certain customers at the expense of the other partners. Also, the CND for a certain customer should not be a static value, but it can change over time. In this way, a customer that is not served in the current solution can be given a higher priority (and therefore a higher probability to be taken into account) during the next day/period.

5.3.2 *Compensation for non-delivery strategies*

Since every partner in the coalition is free to set the CND for each of its customers, and since the CND values have a direct impact on the total cost of the operational solution, the way in which each partner determines its CND values will have a direct impact on the total coalition cost.

On the one hand, each partner will have an incentive to set the CND values for *its* customers to very high values, to ensure that as many of its customers as possible are included in the solution. However, if all partners set very high CND values, the total coalition cost is likely to increase significantly as some — now more expensive — customers will remain unserved. An incentive for partners to keep their CND values low, should therefore be installed. This incentive can be provided by the cost allocation mechanism: partners that consistently set high CND values for their customers should be penalized by being assigned a relatively large share of the total coalition cost. On the other hand, if a partner sets the CND values to very low values (lower than the marginal cost of adding that customer to a route), the customers will remain unvisited as paying the compensation cost will then lead to the lowest total cost. As a result, we encourage the partners to set the CND values close to the marginal cost of serving the customer.

The 'collaborative' selective vehicle routing problem distinguishes itself from the (non-collaborative) SVRP in that the former requires a second issue to be tackled besides solving the routing problem: the allocation of the global coalition cost. The mechanism used to determine each partner's share in this coalition cost is called the *cost allocation method*.

When operating in a collaborative environment, the cost allocation method is therefore interwoven with the vehicle routing solution process. We propose a general approach that, besides solving the traditional (non-collaborative) vehicle routing problem, also takes into account the CND strategy of the individual partners by incorporating a cost allocation mechanism. This approach is visualised in fig. 5.3.

This framework will now be used to analyse the selective vehicle routing problem in a collaborative environment.

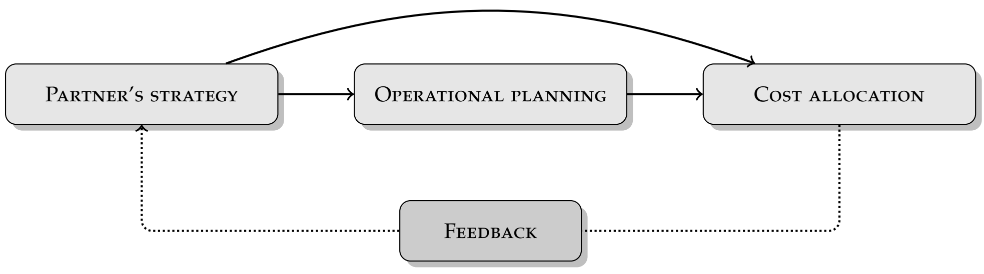


Figure 5.3: The proposed collaborative vehicle routing approach. In a first stage, individual partners decide on their strategy. In a second stage, the VRP is solved. Next, the coalition cost is allocated to the different partners. This allocation will provide feedback to the partners, who may adapt their strategy accordingly.

At the start of the collaboration, each individual partner determines its *strategic position*, i.e., the CND values for its customers (*partner's strategy*). Based on the provided compensations, the selective vehicle routing problem is solved at the level of the coalition (*operational planning*) and a total distribution cost is obtained. This cost is to be allocated to the individual partners (*cost allocation*). The allocation is done by a predefined cost allocation method, and preferably both the obtained operational plan (routes) and the partners' individual strategy should be taken into account. It can be expected that to a certain extent, the different companies in the coalition remain competitors and each partner will therefore evaluate the collaboration in terms of personal gains. The cost allocation mechanism should therefore be chosen in such a way that partners are rewarded if their decisions with respect to the CND values of their customers benefit the coalition.

As the partners' individual CND strategy, and therefore also the operational solution, highly depends on the resulting cost allocation, a *feedback loop* is included. It is expected that partners that are assigned a large share of the coalition cost as a result of exorbitant CND values will adjust their behaviour to avoid incurring such large costs in the future. As this relation is represented with a dotted line, we will not focus on this dynamic character of the problem in this chapter.

The agreement on this long-term joint planning of the distribution activities is aimed at raising the number of served customers using the coalition's limited resources, while reducing costs. The creation of a strategic coalition, however, does not imply that a partner will give up personal objectives nor the lever to guide the global solution into a direction that is desirable from its individual point of view. The degree to which organisations allow a shift in decision-making towards the benefit of the coalition will determine the boundaries of the potential benefits of the coalition (Langley 2000). In the literature, this is referred to as the *flexibility of a partner* (Vanovermeire and Sörensen 2014b). If the flexibility of one of the partners is limited with respect to the operational routing, the opportunities concerning synergy and total efficiency are likely to reduce. In the SVRP, flexible partners are those that set relatively low CND values.

5.3.3 *Cost allocation methods for the* SVRP *in a collaborative environment*

As explained in section 5.3.2, the performance of the coalition depends to a large extent on the partners behaviour and flexibility. To ensure that partners behave and adopt a CND strategy in favour of the coalition, the right incentives should be given by the cost allocation mechanism. We therefore argue that a decision made at the operational (routing) level should affect the cost allocation result and vice versa. This dependency is generally omitted in the existing literature. Furthermore, by ignoring the cost allocation mechanism, it will be impossible for a partner to determine its personal benefits when forming or joining a coalition.

5.3.3.1 *Allocation methods and incentives*

There is widespread agreement on the fact that no single cost allocation mechanism produces a fair cost allocation in all situations. No method can therefore be considered as a global best practice, applicable in every scenario. In Defryn, Vanovermeire, and Sörensen (2015), we argue that a cost (or profit) allocation method should be selected by the coalition, based on the *incentives* that it gives to the individual partners. These should be in line with the coalition's vision on success. In this way, the allocation will force its partners to behave in a way that is perceived desirable for the coalition. The *volume-based profit allocation* for example, will allocate larger profits to the partners that transport the largest volumes. It is not questioned whether this approach is fair, but the clear incentive towards the partners to increase their volumes is undeniable as transporting larger volumes will result in a larger share of the coalition gain.

Although a coalition is free in formulating its preferred incentives, it can be recommended that these incentives should *motivate the partners to adopt a flexible attitude with respect to the routing problem*. By behaving in a flexible way, partners give a large degree of freedom to the coalition, resulting in a more efficient global routing solution.

In the collaborative SVRP discussed in this chapter, the leverage given to the partners is the CND strategy. If all CND values are set equally for all customers, no differentiation exists among the different customers. No detours are to be made in order to include more expensive customers in the solution, and the number of customers served in the solution is maximised — customers are only selected based on their locations — while minimising the total distribution cost. By imposing relatively high CND values to certain customers, the probability of taking these customers into the final routing solution will increase. In this way, a partner is given control on the optimal choice of the routing solution. However, this might be at the expense of global efficiency — less customers can be served with the same resources — and might raise the total coalition cost.

If the CND value of a customer is lower than its minimal marginal transportation cost (distance), it is never profitable to take this customer into the final solution. The minimal marginal transportation cost is defined as the minimal detour that is to be made to include this customer in any existing tour.

In this chapter we investigate the behaviour of two different cost allocation mechanisms for the selective vehicle routing problem in a collaborative environment. First we take a look at the well-known Shapley value cost allocation method, as it is commonly seen as a possible best practice by the industry. Next, these results will be compared with an alternative allocation rule, developed specifically for the SVRP, taking into account both the CND and customer locations.

5.3.3.2 *Shapley value allocation method*

The Shapley value cost allocation method allocates the coalition cost among to coalition partners, based on each partner's *cooperative productivity*. For a more elaborate introduction to the Shapley value, we refer to section 3.3.1

The Shapley value satisfies certain axioms that are generally regarded to be important properties a cost allocation mechanism should posses. These include *symmetry, dummy player property, efficiency* and *additivity* (Nagarajan and Sošić 2008). Furthermore, the Shapley value cost allocation provides a result that is *individually rational* for a superadditive game (Moulin 1988).

As the Shapley value is based on the partners' marginal contribution in every possible subcoalition, it is able to properly capture the financial impact of a single partner on the coalition. Its drawback, however, is the need of information. The calculation of the Shapley value requires at least an estimation of the total cost of every possible subcoalition. This might turn out very challenging or even impossible in practice as no information is available on the decision making and partner behaviour in the unformed coalitions can not be observed directly. It can only be simulated. In this chapter, the simulation is done by the metaheuristic approach described above as the *operational planning is calculated for every possible subcoalition* in order to determine the total cost of these subcoalitions.

Furthermore, in a two-partner coalition, the Shapley value possesses the property of dividing the total coalition gain equally among the collaborating partners, without taking into account the partners' stand-alone efficiency and flexible behaviour towards the coalition. In a two-partner coalition, it therefore loses any lever to stimulate flexibility. A solution for this problem, however, was proposed by Vanovermeire and Sörensen (2014b).

5.3.3.3 CND-*weighted allocation method*

Notwithstanding the popularity of the Shapley value, its generality might prevent it from providing the desirable incentives to its partners. Even if the Shapley value does support the right incentives, this relation might not be that straightforward for the supply chain manager. Therefore, based on the idea of *separable and non-separable costs* (Tijs and Driessen 1986), a cost allocation method is constructed in this chapter that is explicitly based on the partners' CND policy and their customer locations. The CND-weighted cost allocation is constructed as follows.

The separable part of the total coalition cost, i.e., linked to one specific customer (c_i^p) in the tour, consists of the marginal cost m_i of adding this customer to the solution.

For every customer that is served in the final routing solution, the separable cost can be calculated as the difference in total distance if this customer is taken into account or left out of the final tour, without re-optimising the solution.

$$m_i = d_{i-1,i} + d_{i,i+1} - d_{i-1,i+1} \tag{5.9}$$

The remaining part of the coalition cost is called the *non-separable* cost and can be divided in various ways (Cruijssen 2012). In order to align the allocation with the incentives towards flexibility, the non-separable cost will be allocated based on weights, defined by the total CND of the customers of each partner in the final routing solution. The cost allocated to partner p can therefore be written as follows, where $C(N)$ is the total coalition cost, M_p equals the sum of the marginal costs of the customers belonging to partner p and $\text{CND}_{p,\text{sol}}$ represents the sum of all compensations for non-delivery of all customers of partner p that are served in the solution.

$$\psi_p = M_p + \frac{\text{CND}_{p,\text{sol}}}{\sum_p \text{CND}_{p,\text{sol}}}\left(C(N) - \sum_p M_p\right) \tag{5.10}$$

As the CND-weighted cost allocation is completely based on the specific SVRP parameters, the behaviour of the different partners in the coalition can be linked directly to the allocation results. Furthermore, we can state that for the calculation of the CND-weighted cost allocation only the result of the grand coalition is taken into account. Contrary to the Shapley value, the CND-weighted method is not affected by stand-alone efficiency or costs and the performance of subcoalitions. We will show in our simulation results that this will result in a situation where partners with equal flexibility towards the routing solution will *pay the same cost for the same service*. The CND-weighted method does, however, not guarantee individual rationality. To overcome this problem, practitioners might consider our transformation algorithm, introduced in section 3.5.

5.4 Computational experiments

In this section, we study the behaviour of the selective vehicle routing problem in different collaborative scenarios, focusing on the impact of a partner's characteristics and strategy on both the operational solution and the cost allocated to this partner. First, the impact of different CND strategies is investigated. Secondly, we study the effect of different customer location patterns, measuring the influence of the average distance to the depot and the amount of clustering on the final solution.

The simulation is based on a set of generated instances that are available from the authors upon request. All instances are generated on a square grid of width 100, with a central depot located at coordinate $(50, 50)$. Without loss of generality, we assume a three-partner coalition where every partner has 15 customers and brings one single truck into the coalition. Therefore, the number of available vehicles equals the coalition size for every subcoalition. The maximum distance these trucks can travel is limited to 142. All distances are Euclidean.

A fixed CND of 20 is assumed for all customers of partners 2 and 3. For partner 1 different scenarios are considered where the CND for all customers ranges from 4 up to 100. The instances are solved using the metaheuristic approach, described in section 5.2.2, and costs are allocated by both the Shapley value cost allocation and the CND-weighted cost allocation.

The algorithm is coded in C++ (MS Visual Studio) and executed on an Intel (R) Core(TM) i5-3320M @ 2.60GHz with 8GB of RAM under a windows operating system. The results were obtained by running the algorithm and the cost allocation method on a set of 30 different test instances. All reported values are averaged over this set.

5.4.1 *Impact of the compensation for non-delivery value*

As discussed in section 5.3.1 the CND value is used by the partners in the coalition as a way to assign priority to their customers. Therefore, the CND has a direct impact on the optimal routing solution, i.e., the solution with the minimal total distribution cost for the coalition. If all partners assign similar CND values to their customers, no differentiation exists between the partners and the inclusion of customers will be only based on their geographical location in the distribution area. On the other hand, a non-flexible attitude (high CND values) of one of the partners will generally result in a routing solution that is less efficient. In this section, we investigate the sensitivity of the vehicle routing solution to the CND values by means of simulation. For the purpose of these experiments, all customer locations were chosen according to a uniform random distribution.

Figure 5.4 is a visual representation of the number of customers served in the final solution. As no differences in CND strategy exist between partners 2 and 3, both partners are treated equally by the routing algorithm, and they both have approximately the same number of customers in the final solution. If partner 1 also imposes a CND of 20, customers of all three partners appear with equal frequency in the solution.

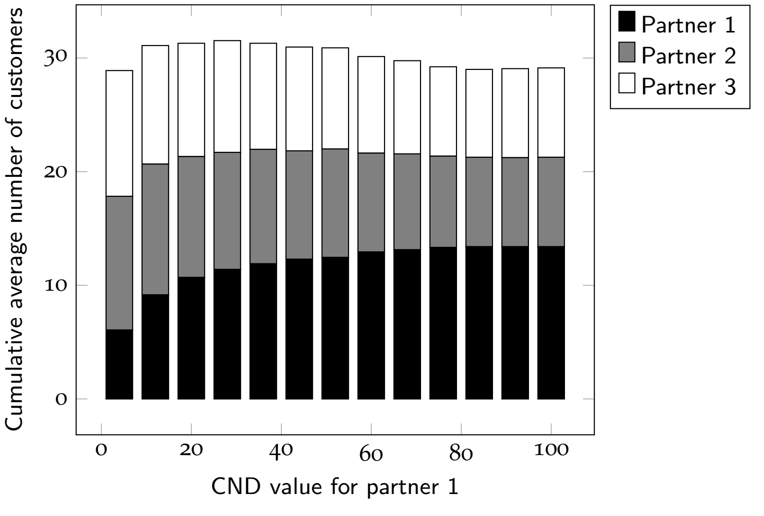


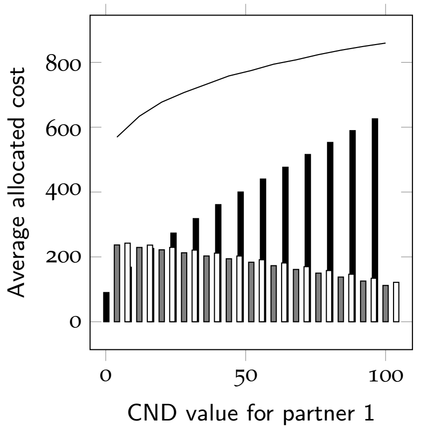
Figure 5.4: Number of customers served in the final solution.

When the CND value of partner 1 increases for all its customers, not serving them becomes more expensive for the coalition so the algorithm will generate a solution in which more of this partner's customers are visited, at the expense of the other partners' customers, that are now served less frequently. Additionally, the inflexible strategy of partner 1 will result in an increased total coalition cost (see fig. 5.5). The coalition as a whole is now functioning in a less efficient way, and partner 1 should be discouraged from setting high CND values by the cost allocation mechanism.

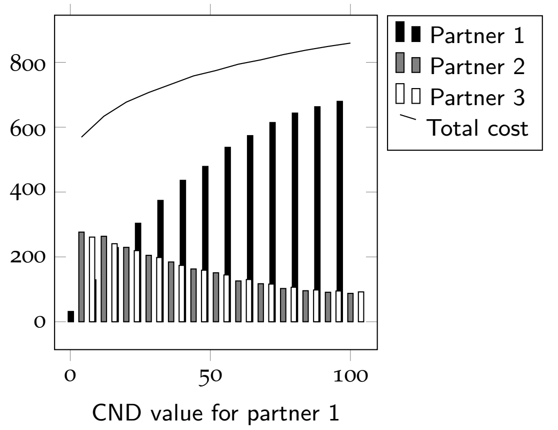
When the CND values of partner 1 are much lower than those of the other partners, a drop in the total number of customers served in the final solution can be witnessed.

The reason for this is twofold. First, the decreased CND values of partner 1 render it less expensive to leave this partner's customers unserved. As a result, also the total coalition cost decreases because a low CND is to be paid for the non-served customers of partner 1. Second, a customer will only be visited if its CND cost is higher than its marginal (distance-based) cost in the trip. For very low CND values it will therefore be less costly to pay the compensation fee than to drive the additional distance to keep the customer in the route.

The resulting cost allocations are shown in fig. 5.5. When no differences exist between the partners (all have a CND of 20), both allocation mechanisms divide the costs equally. Also, when partner 1 behaves in a less flexible way than the other partners, this results in a larger total coalition cost (represented by the black line), and both the Shapley value and the CND-weighted cost allocation consequently assign a larger share of the cost to this partner. Where the allocated cost increases linearly by applying the Shapley method, the CND-weighted cost allocation tends to follow more the underlying number of customers that are served for every partner. We can conclude that the Shapley value punishes the inflexible behaviour directly, whereas the CND-weighted approach punishes the inflexible behaviour through its effects on the grand coalition and the number of customers served for every partner.



(a) Shapley value Cost Allocation



(b) CND-weighted Cost Allocation

Figure 5.5: Cost allocated to the partners by both cost allocation mechanisms for varying CND levels of partner 1.

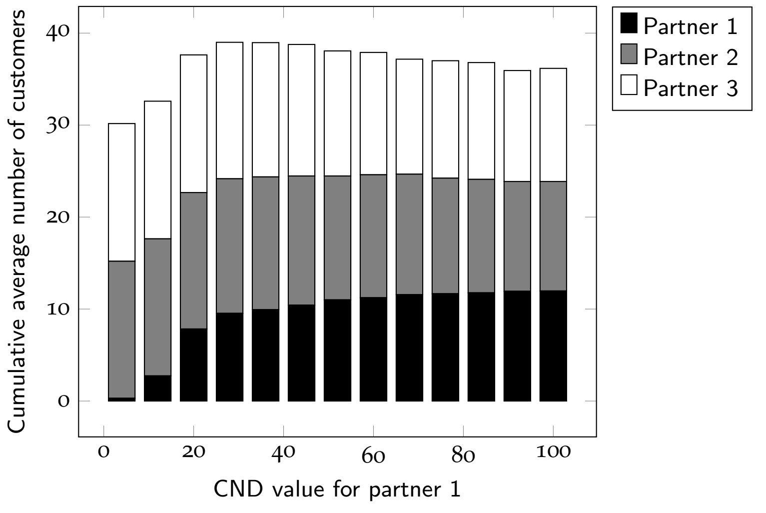


Figure 5.6: Number of customers served in the final solution.

5.4.2 *Varying average distance between customers and depot*

The algorithm for the routing problem preferably serves customers that (i) have large CND values, and (ii) increase the total distance of the solution as little as possible. For this reason, customers that are located close to the depot will tend to be served with a larger probability than customers located far away. In this section we study the impact of the location of a partner's customer within the distribution area and the interdependency with the CND strategy.

In our simulation, a square area of size 50 around the depot is defined. The customers of partners 2 and 3, all having a CND equal to 20, lie inside this smaller area and, therefore, closer to the depot. The customers of partner 1, again with a variable CND, are all located outside this smaller area, and are therefore located further away from the depot.

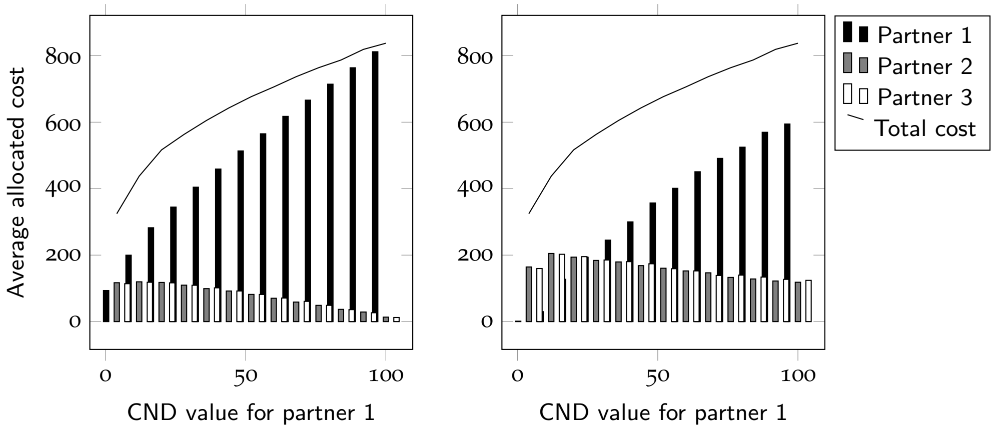
It can be expected that customers located closer to the depot are more likely to be served in the final routing solution. Due to a reduction in travel distance between these customers and the depot, one vehicle will be able to serve more customers without violating the maximum vehicle distance. If all customers, including those of partner 1, have a CND of 20, customers of partners 2 and 3 will have a larger probability of being served, which can also be seen in fig. 5.6.

The vehicles are preferably used to serve the customers that are located close to the depot. In order to include the customers of partner 1, which are located further away, a detour is to be made. For very low CND values, including these customers is not profitable as the cost of not serving them is lower than the detour to be made. In order to make the longer trips towards partner 1's customers more attractive for the coalition, this partner needs to impose larger CND values. However, this behaviour will render the solution both more expensive and less efficient. For this reason, we expect the inflexibility of partner 1 to be punished by the cost allocation mechanism.

The results of both the Shapley value and CND-weighted cost allocation are visualised in fig. 5.7. We can see that in both methods, the inflexible behaviour of partner 1 is punished by an increase in allocated cost. A very high cost, up to almost 100% of the total coalition cost, is allocated to partner 1 by applying the Shapley value method. This can be explained as follows. As the customers of partner 1 are located far away, the stand-alone cost of this partner will be significantly larger. Furthermore, adding partner 1 to any subcoalition will reduce the efficiency and raise total cost significantly. For a further increase in CND, a negative allocated cost will be obtained for partners 2 and 3, stating that they will receive money for joining the coalition while partner 1 pays more than the total coalition cost. Notwithstanding this (potentially undesirable) behaviour, the Shapley value cost allocation does remain individually rational, i.e., each partner is allocated a lower cost than its stand-alone cost.

As the CND-weighted cost allocation method is only based on the cost that the partners induce in the final routing solution, the cost allocated to partner 1 tends to be small for the scenarios where less customers of this partner are served in the routing solution. This is the case for scenarios where partner 1 is behaving in a flexible way (low CND). Even if partner 1 behaves in a very inflexible way, still many customers of partner 2 and 3 remain served because of their attractive position close to the depot. This is captured more directly by the CND-weighted method. Here again we conclude that the CND-weighted cost allocation remains closely bound to the underlying operational solution.

Contrary to the Shapley value cost allocation, the CND-weighted method does not guarantee individual rationality. As the outcome of this method is only based on the final routing solution, it does not take into account the stand-alone costs. The cost allocated to a partner is largely defined based on the number of customers served



(a) Shapley value Cost Allocation (b) CND-weighted Cost Allocation

Figure 5.7: Cost allocated to the partners by both cost allocation mechanisms for varying CND levels of partner 1.

in the routing solution of the coalition, weighted according to the corresponding CND. In this case, the customers of partners 2 and 3 are located close to the depot. Notwithstanding the maximum vehicle distance that is imposed, these partners can already serve a majority of their customers in the stand-alone scenario. As a result, only very little (and sometimes zero) customers (with their CND) remain unserved, and the stand-alone costs of partners 2 and 3 are very low. Due to this, the costs allocated to partners 2 and 3 can easily exceed their stand-alone costs and the property of individual rationality is not guaranteed. We look into this in more detail in section 3.5.2.

5.4.3 *Customer clustering*

In the third simulation scenario, we look at the effect of geographical clustering of customers. If the customers belonging to each partner are located in close proximity to one another and no (or limited) geographical overlap exists between the customer clusters of the different partners, no significant collaboration synergy can be expected. If a coalition should be formed between such incompatible partners, we expect its coalition cost to be not much less than the sum of the stand-alone costs.

A set of test instances was generated in which all customers belonging to one partner are located in the same part of the distribution area. In this way, customers of partner

1 are located in the North-West, those of partner 2 in the North-East and finally those belonging to partner 3 in the South. Customers of partner 3 are generated to be on average closer to the depot than the ones of the other companies.

Based on the characteristics of the test instances, the distance between the depot and the customer clusters, and between the different clusters is high, compared to the distance between the customers within one cluster. As a consequence it will be very expensive to combine customers of different clusters into one vehicle. As the customers of partner 3 are located on average closer to the depot, this single vehicle can be used to serve more customers compared to the other partners, as seen in fig. 5.8.

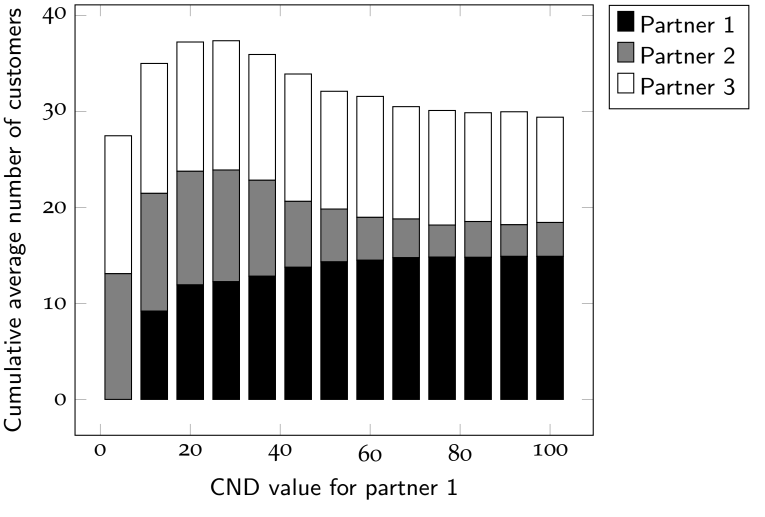
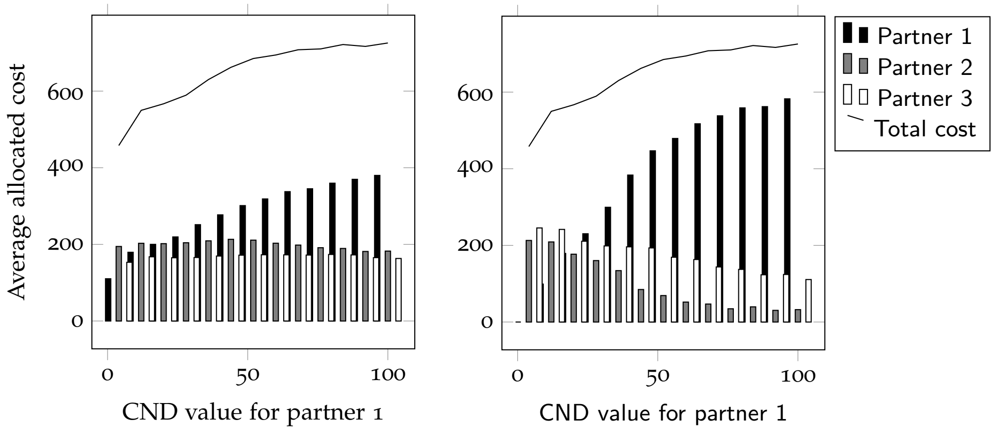


Figure 5.8: Number of customers served in the final solution.

As the customers of partner 1 will become more and more expensive for increasing values of this partner's CND, the detour of visiting two different clusters with one vehicle might become more attractive in order to avoid the larger compensation costs that should be paid if the customers remain unvisited. However, this action renders the solution less efficient (less customers can be visited), and we expect this inflexible behaviour to be punished again by the chosen cost allocation mechanism. As customers of partner 2 are located further away compared to those of partner 3, the cluster of partner 2 has a lower probability to be visited by a vehicle. This can be seen in fig. 5.8.

The resulting cost allocation is shown in fig. 5.9. At first sight it can be seen again that partner 1 was charged a larger relative part of the total coalition cost for increasing values of its CND. This scenario, however, reveals another difference in approach for both cost allocation mechanisms studied in this chapter.

When comparing the relative cost allocated to partners 2 and 3, the Shapley value cost allocation charges a larger cost to partner 2 (fig. 5.9a), while this partner is favoured in the CND-weighted cost allocation mechanism (fig. 5.9b). This can be explained as follows. As customers of partner 3 are located on average closer to the depot, these customers can be served with higher efficiency. Therefore the stand-alone cost of partner 3 will be lower compared to that of partner 2. Moreover, this high efficiency will be present in every subcoalition. As the Shapley value takes this into account, a lower cost is allocated to partner 3 although a larger number of customers of this partner are served in the final solution. In the CND-weighted cost allocation however, costs are allocated based on the impact of every partner on the final routing solution. Because no differentiation exists in the CND of customers of partners 2 and 3, both partners are treated equally. As more customers of partner 3 are taken into the final routing solution, this partner should pay a larger share of the total cost.



(a) Shapley value Cost Allocation

(b) CND-weighted Cost Allocation

Figure 5.9: Cost allocated to the partners by both cost allocation mechanisms for varying CND levels of partner 1.

5.5 Conclusions and future research

In this chapter we took a closer look at how a selective vehicle routing problem can be used in a collaborative environment. Besides the vehicle routing problem itself, the collaborative environments force the coalition to consider the problem of strategic positioning, as well as the allocation of the coalition cost.

In order to solve the selective vehicle routing problem, a randomized, multi-start variable neighbourhood metaheuristic was developed. Concerning the cost allocation, we discussed two different approaches: the Shapley value cost allocation, a widespread game-theoretical approach, and a new CND-weighted cost allocation mechanism that could be linked directly to the problem definition of the SVRP.

The solutions of the routing and cost allocation problems are both dependent on a third aspect, the strategic behaviour of the partners with respect to the collaboration. This behaviour was captured by the compensation for non-delivery (CND), the cost that is to be paid if a customer is not selected for delivery in the routing solution. We demonstrated that the strategic behaviour of the partners has a large influence on the efficiency of the routing solution. By choosing a cost allocation mechanism, the coalition implicitly formulates incentives that it perceives important. These incentives should stimulate the partners to behave in a flexible way towards the coalition in order to assure maximum efficiency of the logistical planning. Partners that tend to pull the solution away from its optimal working point, by behaving in an inflexible way, should also accept the consequences in terms of a larger allocated cost. This strong relationship between partners' behaviour, routing solution and cost allocation is often omitted in the literature, resulting in an incomplete view of the collaborative vehicle routing problem. By means of simulation, these dependencies were shown and tested on different sets of instances.

In a first simulation, the effect of the partners' CND strategy on the final routing solution and cost allocation was investigated. A partner that imposes relatively larger compensations for non-delivery increases the probability that its customers are taken into the final routing solution. However, this non-flexible attitude will raise total coalition cost while serving less customers and should therefore punished in the cost allocation. The Shapley value and CND-weighted cost allocation behave similarly in this collaborative environment. The CND-weighted method tends to follow more the number of customers visited for every partner.

If the customers of one partner are more favorably located than those of the others, this pattern will also be found in the solution. The other partners can compensate by setting higher CND values, in which case an inferior routing solution will be chosen where a detour is made in order to visit the more expensive customers. In this simulation the severity of the Shapley value with respect to the non-flexible partners becomes visible to the extent that relative cost allocations above 100% and below 0% are possible. As this might not be the preferred scenario, the Shapley value still assures an individually rational solution, which is not guaranteed when using the CND-weighted allocation method.

The same conclusion can be drawn from the third simulation, where customers of different partners were clustered in different geographical regions. As this reduces the ability to combine customers of different partners into one trip, the trucks will choose a direction towards the area(s) where more expensive customers are located. Only when relatively high CND values are charged in one area does the solution change to visit this region. This is however at the expense of a larger total coalition cost. Here, the fundamental differences between the two cost allocation methods become clearly visible. While the Shapley value is based on the partners productivity in every possible subcoalition, the CND-weighted cost allocation is only based on the final solution of the coalition. It is up to the collaborating partners to evaluate which approach they perceive as fair.

In this chapter, we focused on the selective vehicle routing problem and introduced a basic framework (solution approach) that can be used to analyse the vehicle routing problem in a collaborative environment. The study is currently limited to the static approach, in which the problem is solved only once. Although we identified the feedback loop, it is not taken explicitly into account. A dynamic (multi-period) approach, where partners might adopt their strategy and behaviour in every period, can be valuable future research.

Furthermore, we plan to study other variants of the vehicle routing problem in a collaborative environment. A different vehicle routing problem will require an alternative definition of partner behaviour and therefore also of the idea of flexibility. We will also examine the behaviour of what we define as *multi-objective collaborative vehicle routing problems*. Here, the partners have different and possibly conflicting objectives with respect to an optimal routing solution (e.g., total distance, time window violation,...) which should be combined into a single (cooperative) optimization problem.

Part III

THE INCLUSION OF INDIVIDUAL PARTNER OBJECTIVES IN LOGISTICS OPTIMISATION MODELS

6

Models for multi-objective optimisation

Abstract:
This chapter considers a horizontal logistics cooperation in which multiple companies (called partners) jointly solve a (collaborative) vehicle routing problem. To capture the individual partner interests in the logistics optimisation model, we allow each individual partner to set its own set of objectives. In such a situation, the question arises whether only these individual partner objectives should be considered during the optimisation of the collaborative optimisation problem (the partner efficiency model), or whether a set of coalition objectives should be defined first (the coalition efficiency model). This chapter investigates the merits and drawbacks of both approaches by applying them to a collaborative variant of the well-known travelling salesman problem with soft time windows.
Our results confirm that, even in a situation in which each partner has multiple objectives, joining a horizontal logistics coalition is beneficial for all partners. We further conclude that the coalition efficiency model is able to find good quality solutions with less calculation time, but lacks robustness. The partner efficiency model, on the other hand, is able to provide the decision maker with a better Pareto front approximation, at the expense of a higher complexity.

6.1 Introduction

The current research on horizontal logistics cooperation is focused mainly on assessing the costs and benefits, and the allocation of these benefits among the individual collaborating partners. It is striking that only a limited number of papers address operational planning problems in horizontal logistics cooperation (see Verdonck et al. (2013) for an overview). Also, when quantifying the cost saving of such logistics collaborations, existing models do not take into account to which partner a transportation request originally belonged. It is even not acknowledged that all transportation requests actually belong to multiple companies. Therefore, no distinction is made between the objective of the coalition of collaborating companies and the objective of each individual company. Although the coalition as a whole should perform as efficiently as possible to exploit the synergies from the collaboration, all collaborating partners remain independent entities that tend to favour a solution that is best according to their own objectives.

With this chapter, we are the first to argue the objectives of both levels should be taken into account. In section 6.2, the current state of the art in operational optimisation within horizontal logistics cooperation is summarised. In section 6.3 our problem is defined and the two levels of decision making (the level of the coalition versus the individual partner level) are introduced and in section 6.4 the multi-objective travelling salesman problem with soft time windows is introduced. We propose two solution approaches for tackling multi-objective optimisation in a horizontal logistics cooperation in this chapter. Both methods, the coalition efficiency model and the partner efficiency model, are described in section 6.5 and section 6.6 respectively. In section 6.7 we will provide the interested reader more insight in our implementation of the Shapley value cost allocation method after which we present our computational results in section 6.8. Finally, we conclude this chapter with section 6.9.

6.2 Literature review

In the literature on the operational aspects of horizontal logistics optimisation, two main approaches are distinguished: order sharing and capacity sharing (Verdonck et al. 2013). In the first approach, each collaborating partner can decide to share (a selection of) its customer orders with the group. These pooled orders are then reallocated to the available vehicle trips. When the optimisation is done by solving one large-scale vehicle routing problem from the point of view of a centralised decision maker, this is referred to as *joint route planning* (Cruijssen et al. 2007). Another commonly used technique to reallocate customer orders is an *auction-based mechanism*, in which partners can bid on the pooled orders. See for example the framework provided by Dai and Chen (2011). In a second approach, companies can decide to share their vehicle capacities. In this way the capital investment associated with these vehicles can be split among multiple partners (Verdonck et al. 2013). This approach is, however, less common in the literature.

Because the current chapter wants to study decision making of the coalition and its constituting partners, this section will examine the structure of existing optimisation models in both approaches to horizontal logistics collaboration. Usually, the benefits of horizontal logistics cooperation are quantified by comparing the logistics planning with and without collaboration. To obtain the collaborative solution, a logistics optimisation problem is to be defined and solved for the group of collaborating partners. Using the Web of Science[1], 59 journal publications on the topic of 'horizontal cooperation' (or 'horizontal collaboration') and 'logistics' are retrieved. Careful screening on the title and the abstract yielded a subset of 20 papers for further study. To ensure that the literature search was exhaustive, we also performed an additional manual search using the same keywords, resulting in a final set of 24 publications.

All studied papers are listed in table 6.1. Each reference is categorised by the objective function used in the logistics optimisation model and the way in which the individual partner interests are handled by the authors. For the objective functions, four main approaches can be distinguished among of which the minimisation of the distance-based routing cost *(min. dist.)* and the minimisation of the total logistics cost *(min. TC)* are the most common. Typically, this total logistics cost consists of the distance-based cost added with additional factors such as a time-based cost (Adenso-Díaz, Lozano, and Moreno 2014; Dahl and Derigs 2011; Lozano et al. 2013), penalties for empty trips or non-delivery (Adenso-Díaz, Lozano, and Moreno 2014; Defryn, Sörensen, and Cornelissens 2016; Hezarkhani, Slikker, and Van Woensel 2016; Lozano et al. 2013), additional linking costs when combining multiple transportation requests (Adenso-Díaz et al. 2014) or costs related to the use of DCs and warehouses (Verdonck et al. 2016; Wang and Kopfer 2015). Vanovermeire et al. (2014) adopt an alternative approach in which the cost of a trip between two locations is calculated by means of a pace list, and depends therefore on the load of the vehicle. The optimisation model therefore requires the solution of a bin packing

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problem in which the number of required vehicles is minimised *(min. veh.)*. Instead of minimising the transportation cost, some authors aim at maximising the total profit *(max. prof.)* of the coalition (Berger and Bierwirth 2010; Li, Rong, and Feng 2015; Yang et al. 2015). Requiring that all transportation requests are executed, this approach is equivalent to the minimisation of the logistics costs.

Models that focus only on the global performance of the group, ignore the effect of the operational decisions on the goals of the individual partners. As the collaborating partners remain independent entities, it is likely to assume that they will (also) evaluate the performance of the coalition in terms of personal gains. In all selected contributions, a (single) objective function is defined at the level of the coalition. The interests of the individual partners in the coalition are either included as a constraint in the logistics optimisation model *(constr.)*, considered through a compensation mechanism *(comp.)*, handled as a post-processing step after solving the model *(post)*, or not addressed at all *(not)*. A solution framework that adds individual partner interest as a model constraint is proposed in Vanovermeire and Sörensen (2014a). By including a cost allocation mechanism, it is ensured that an individual partner is rewarded for allowing a shift in delivery date so the coalition can achieve a better solution. The inclusion of a compensation mechanism is typically considered in auction-based models when partners can bid on individual transportation requests. A transfer price is then taken into account together with each order exchange. In most chapters that take the individual partner interests into account, a cost allocation method is added to the solution procedure as an independent post-processing step.

Surprisingly, in none of the studied chapters, the individual partner interests are considered in the objective function of the logistics optimisation model. It can however be expected that not all objectives are shared among the collaborating partners or receive the same weight. It is possible for example that respecting time windows is more important for one partner, while the other partners prefer only the lowest cost. Also, a partner might prefer a solution in which the cost allocated to him is minimised above a solution with the lowest total cost for the coalition as a whole. We refer to Bailey, Unnikrishnan, and Lin (2011), for a logistics optimisation model for a group of companies in which the benefits for only one partner of interest are maximised.

The research is also closely related to the challenges faced by the *neutral trustee* in the collaboration. The neutral trustee is a third party that coordinates the cooperation is such a way that all partners are satisfied, and guarantees that no sensitive

Table 6.1: Classification of the studied literature.

	Objective				Partner interests			
Reference	min. dist.	min. TC	min. veh	max. prof.	constr.	comp.	post	not
Cruijssen et al. (2007)		✓						✓
Krajewska et al. (2008)	✓						✓	
Berger and Bierwirth (2010)				✓			✓	
Dahl and Derigs (2011)		✓				✓		
Lozano et al. (2013)		✓					✓	
Adenso-Díaz, Lozano, and Moreno (2014)		✓						✓
Adenso-Díaz et al. (2014)		✓						✓
Juan et al. (2014)	✓							✓
Vanovermeire et al. (2014)			✓				✓	
Vanovermeire and Sörensen (2014a)		✓			✓			
Wang and Kopfer (2014)		✓						✓
Flisberg et al. (2015)	✓						✓	
Li, Rong, and Feng (2015)				✓		✓		
Pérez-Bernabeu et al. (2015)	✓							✓
Wang et al. (2015)		✓					✓	
Wang and Kopfer (2015)	✓					✓		
Yang et al. (2015)				✓		✓		
Defryn, Sörensen, and Cornelissens (2016)		✓					✓	
Guajardo, Jörnsten, and Rönnqvist (2016)	✓						✓	
Hezarkhani, Slikker, and Van Woensel (2016)		✓					✓	
Kimms and Kozeletskyi (2016a)	✓						✓	
Verdonck et al. (2016)		✓					✓	
Yin, Lyu, and Chuang (2016)		✓						✓
Zibaei, Hafezalkotob, and Ghashami (2016)	✓						✓	

information is disclosed among the different (and possibly competing) companies in the collaboration. Bringing potential partners around the table, one of the main challenges of the neutral trustee is to unite and look after the interests of each individual partner. The models presented in this and the following chapters can be useful tools to support the related decisions.

6.3 Problem statement

In all existing approaches, the logistics optimisation problem is defined at the level of the coalition, with only one global objective. In this case, the collaborative problem definition is obtained by combining all transportation requests of the individual partners into one large optimisation problem for which one or more global objective functions, which we will refer to as *coalition objectives*, are defined. As a consequence, the multi-partner context and individual partner characteristics are ignored and it is assumed that all partners agree on one set of global objectives. Although it is reasonable that partners in a horizontal coalition have a common goal and vision on when a cooperation is successful, it should not be ignored that each individual partner remains an independent entity that will evaluate the performance of the coalition mainly in terms of personal gains.

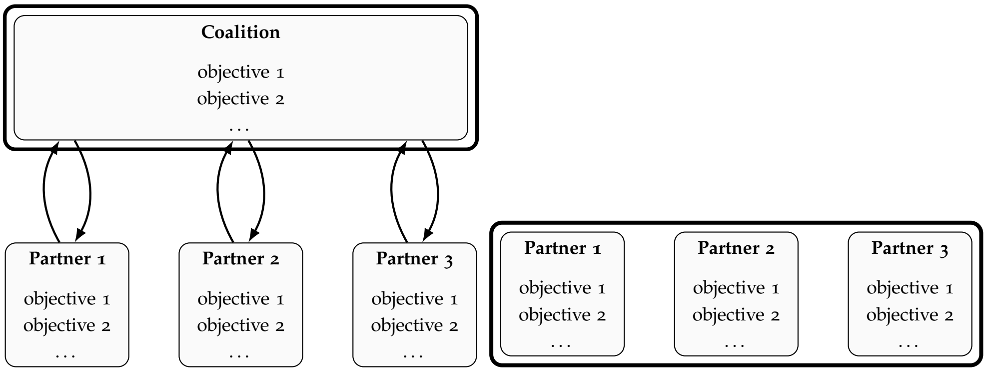
By aggregating the transportation requests of all individual partners and deciding on a global set of (coalition) objectives, the logistics planning can be optimised using any existing, non-collaborative optimisation technique. Importantly, however, coalition objectives are *virtual* objectives in the sense that these objectives have been artificially defined to solve the collaborative routing problem. For none of the partners, the coalition objectives themselves are important, but a solution will only be accepted or rejected by a partner based on the objectives of that individual partner (which we call *partner objectives*).

To allow for the evaluation of all partner objectives, an allocation rule is to be defined to redistribute the obtained results at the coalition level to all individual partners. For example, if the coalition objective is to minimize total time window violation, each individual partner can easily derive the time window violation at its own customers from the overall solution. Other types of coalition objectives, most notably the total cost, time or total distance travelled cannot be trivially distributed among the partners and require an *allocation mechanism*. Several *cost allocation mechanisms* have been proposed in the literature, some simple (e.g., allocate the cost proportional to the amount of goods transported for each partner), other more complicated and grounded in game theory. As argued in Defryn, Sörensen, and Cornelissens (2016) and Defryn, Vanovermeire, and Sörensen (2015) the cost allocation mechanism can provide an incentive to the partners to favour the coalition's objectives as it can be used as a leverage to increase the flexibility of the partners. A partner is considered flexible if he is willing to (partially) sacrifice his own objectives in favour of the coalition.

An important question arises whether this allocation rule and the evaluation of the individual partner objectives should be executed *after* the best solution for the coalition has been found, or *during* the search. In Vanovermeire and Sörensen (2014a), it has been demonstrated that the best solution found using the coalition objective is not always equal to the best solution found using the partner objectives, i.e., when for example the cost is divided *during* the search. In other words, when the optimisation process takes the individual partner objectives into account while looking for a good solution, the final result is generally better for all partners, at the expense of larger computing times. Vanovermeire and Sörensen (2014a) only considered the situation in which all partners have the same single objective, to minimize their total cost. This chapter proposes an extension to the analysis in Vanovermeire and Sörensen (2014a) for situations in which each partner may have multiple conflicting objectives.

When multiple partners, each of which have multiple objectives, jointly perform their operational planning, two options arise. A first option is that the coalition first defines a set of global coalition objectives, encompassing all objectives of all partners, then finds a solution or a set of non-dominated solutions for these global objectives, and then divides the objectives (costs) back to the individual partners. We call this approach the *coalition efficiency model*. The second option is to consider all individual partner objectives and find a set of non-dominated solutions for each individual partner, without first aggregating them into coalition objectives. We call this approach the *partner efficiency model*.

The main research question of this chapter is to find the benefits and drawbacks of either models, and find out which one performs best. Both methods are described in more detail by applying them to the *travelling salesman problem with soft time windows* (TSPSTW). This problem has the advantage of being well-known, and has been chosen mainly for illustrative purposes. Both models, however, are generic and applicable to any collaborative planning problem.



(a) The coalition efficiency model

(b) The partner efficiency model

Figure 6.1: Difference between the coalition efficiency model and the partner efficiency model. The bold box indicates where the optimisation problem is solved.

The following Sections of this chapter are organized as follows. In section 6.4, we describe the TSPSTW and its collaborative variant, the Collaborative Travelling Salesman Problem with soft time windows (COLTSPSTW). The coalition efficiency model and the partner efficiency model, are introduced in section 6.5 and section 6.6 respectively. In section 6.7 we will elaborate on the way the Shapley value cost allocation method is implemented in our algorithms. Afterwards, the coalition efficiency model and partner efficiency model are tested on a set of collaborative TSPSTW instances. The results of these experiments can be found in section 6.8. Finally, section 6.9 summarises the main conclusions.

6.4 Case: the multi-objective travelling salesman problem with soft time windows

In this section, we first explain the specific variant of the TSPSTW used in this chapter, and then extend it to a collaborative scenario, resulting in a problem that we call the COLTSPSTW. This problem will be used as an explanatory example throughout the following sections of the chapter.

6.4.1 *Stand-alone scenario: The travelling salesman problem with soft time windows*

In our TSPSTW variant, each partner operates from its own central depot, from which goods are delivered to a set of clients in a single tour. Client orders are assumed to be small (e.g., parcel delivery), so the vehicle's capacity will not constrain the operational planning. However, for each individual client a time window, during which the goods should be delivered, is predefined. The underlying operational problem for every partner can be modelled as a travelling salesman problem with soft time windows (TSPSTW).

We are given a complete directed graph with a set of vertices representing the depot and all clients to be served, and a set of arcs connecting these vertices. Furthermore, a service time and a time window are defined for every vertex, including the depot. The service time models the time the driver is expected to spend at the client's location for loading, unloading, or providing a certain service. The time window is defined by the client's ready time and due time. Arriving at the client's location before its ready time is allowed, although the vehicle has to wait until the start of the time window before the service can start. Arriving too late, or not being able to finish the service before the due time, results in a *time window violation*. The goal is to construct a Hamiltonian cycle, a path that starts and ends at the partner's depot and in which every customer is visited exactly once.

The problem has two objectives:

1. The minimisation of the total distance travelled.

2. The minimisation of the summed time window violations over all the partner's clients.

Both objectives are conflicting, in that a smaller total time window violation can be achieved at the expense of a larger distance travelled and vice versa.

The idea of soft time window can be linked directly to the concept of *flexibility* (Vanovermeire and Sörensen 2014b). If the time windows are very strict, the degree of freedom in the planning is limited. This will result in a longer total distance travelled in order to make sure that all clients are visited on time. The more a company is able and willing to extend the time windows or allow a certain time window violation, the more freedom it creates to reduce the total travelled distance by changing the positions of the clients in the trip.

In this chapter, we adopt a multi-objective approach for solving the TSPSTW and no a-priori decision is made on the relative importance of both objectives. Instead of constructing one single (optimal) solution, the aim is to generate many solutions that are Pareto-optimal with respect to both objectives. We leave it to the decision maker to select the most preferred solution from this set, based on other criteria. This decision is however out of the scope of this thesis.

6.4.2 *Collaborative scenario: The collaborative travelling salesman problem with soft time windows*

Instead of one company optimising its logistics activities individually, a horizontal logistics cooperation is considered here. A two-partner example is visualised in fig. 6.2. Here, the partner's depots are denoted by the squares, while the circles represent the customers. For visualisation purposes, only the total distance minimisation objective is considered. As stated in the previous section, the logistics planning for each individual partner is modelled as a TSPSTW. From the moment that *geographic similarity* (the degree of overlapping geographic coverage between the co-operating partners) exists, it is likely that synergies can be exploited by allowing certain customers to be served by another partner's vehicle (Raue and Wallenburg 2013). The collaborative problem that appears at the level of the coalition is a *multi-depot multi-travelling salesman problem with time windows*. This problem is closely related to the multi-depot vehicle routing problem (we refer to Montoya-Torres et al. (2015) for an extensive literature review). However, no customer demands are considered and no capacity restrictions are provided for the vehicles in our problem formulation. In what follows, we will therefore refer to our problem as the *collaborative travelling salesman problem with soft time windows* (COLTSPSTW).

The main question is which objective(s) to use when solving the COLTSPSTW. A first approach assumes that all partners agree on a common goal and are able to define a set of global coalition objectives. Based on the stand-alone scenario and the similarity between the individual partners, we suggest the following two coalition objectives:

1. The minimisation of the total distance travelled by all coalition partners.

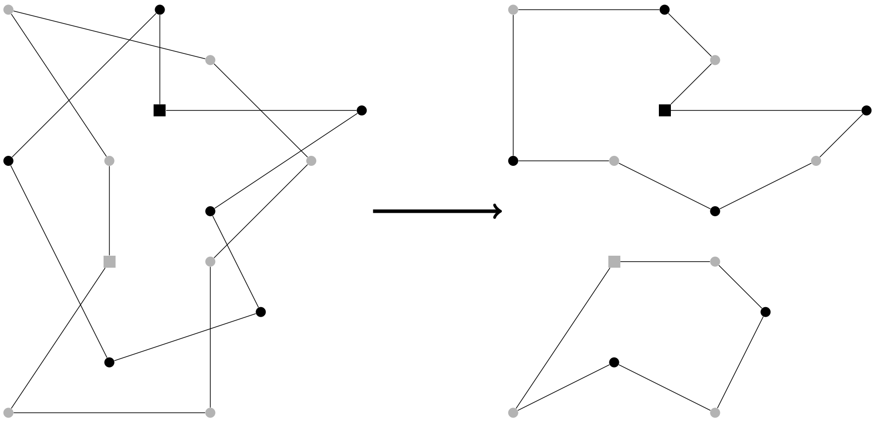


Figure 6.2: The collaborative travelling salesman problem with soft time windows for a two-partner (black and grey) horizontal cooperation.

2. The minimisation of the summed time window violations over all clients of all partners in the coalition.

As a result, we consider the coalition to be a single entity and the fact that clients belong to different companies has no importance any more. We say that we optimise towards *coalition efficiency*, i.e., make the coalition as a whole as efficient as possible. This idea forms the basis for the *coalition efficiency model*, described in section 6.5.

A second approach acknowledges that all partners remain independent companies that have individual objectives. Every solution constructed for the coalition is then evaluated by each individual partner with respect to their own objectives. For the COLTSPSTW, we can assume that each partner has the following objectives:

1. The minimisation of the summed time window violations *of its own clients*.

2. The minimisation of its own *allocated share* of the total logistics cost

A solution that is acceptable for one partner (i.e., it is in the Pareto set for this partner's objectives) may not be so for the other partners. A good solution for the coalition should therefore be a compromise with respect to all individual partner objectives, and should be in the Pareto sets of all partners in the coalition. In this case, we talk about optimisation with respect to *partner efficiency*. We will elaborate on this idea in section 6.6.

6.5 Coalition efficiency model

A solution is considered *coalition efficient* if it is in the Pareto set of non-dominated solutions with respect to the coalition objectives. Based on this idea and the collaborative vehicle routing approach proposed by Defryn, Sörensen, and Cornelissens (2016), the coalition efficiency model is defined as a four-step approach.

- **step 1:** Aggregate and redefine the logistics problem at the level of the coalition.
- **step 2:** Construct an efficient solution set for the coalition as a whole.
- **step 3:** Project the solutions obtained during step 2 on the individual partner objectives using predefined allocation rules.
- **step 4:** Evaluate the Pareto efficiency of each solution according to each of the partner objectives. Only solutions that are marked as efficient by every partner are kept in the final solution set of the collaborative problem.

In the following sections, we will elaborate more on each step of the coalition efficiency model by applying it to the COLTSPSTW.

6.5.1 *Step 1: Aggregation*

The goal of this first step is to redefine the logistics problem at the level of the coalition. All transportation requests, networks and available resources of the individual partners are aggregated into one optimisation problem. To determine the objective function of the coalition, it is assumed that all collaborating partners agree on a single set of coalition objectives. In this way, the multi-partner logistics problem is transformed into a traditional, non-collaborative problem. Similar to the stand-alone scenario of each partner, the coalition objectives for the COLTSPSTW are considered to be (i) the minimisation of the total distance travelled by all vehicles (total coalition cost), and (ii) the minimisation of the total time window violation over all customers.

In our definition of the COLTSPSTW, the partners are homogeneous, i.e., they have the same set of objectives. This is, however, not a requirement of the coalition efficiency model. In general, any combination of partners can be considered, as long as a common set of objectives can be negotiated (which will become more difficult, of course, as the individual partner objectives diverge).

6.5.2 *Step 2: Optimisation at the coalition level*

In this phase, the aggregated model defined in step 1 is solved by using any available (non-collaborative) logistics optimisation technique. As two coalition objectives are identified for the COLTSPSTW, a multi-objective optimisation method is required that will return a Pareto set. We suggest a multi-directional local search metaheuristic, based on the idea of Tricoire (2012), which is introduced in more detail in what follows.

6.5.2.1 *Metaheuristic overview*

A visualisation of the solution procedure is visualised in fig. 6.3. First, an initial solution set is constructed by the algorithm. Three different construction strategies are used in order to diversify the solutions in the initial set: *nearest neighbour*, *sorted by ready time* and *sorted by due time* (see table 6.2). Afterwards, each solution is improved with respect to each objective function by means of local search. In other words, a local search is performed for every solution–objective combination.

Table 6.2: Construction strategies.

Strategy	**Definition**
NEAREST NEIGHBOUR	Start from an unused depot and iteratively add the closest unvisited customer to the trip. An equal number of customers is added to each trip.
SORTED BY READY TIME	Add all customers from a single partner to a trip and sort them according to their ready time.
SORTED BY DUE TIME	Add all customers from a single partner to a trip and sort them according to their due time.

The improved solution S' can either dominate S or both solutions can be Pareto-efficient. After having improved all initial solutions, the dominated solutions are discarded and the search continues with all non-dominated solutions. In this way, we also allow the size of the Pareto frontier to increase/decrease. The search is ended by the stopping criterion, predefined as the maximum allowed calculation time. Then, the current Pareto frontier is returned by the algorithm.

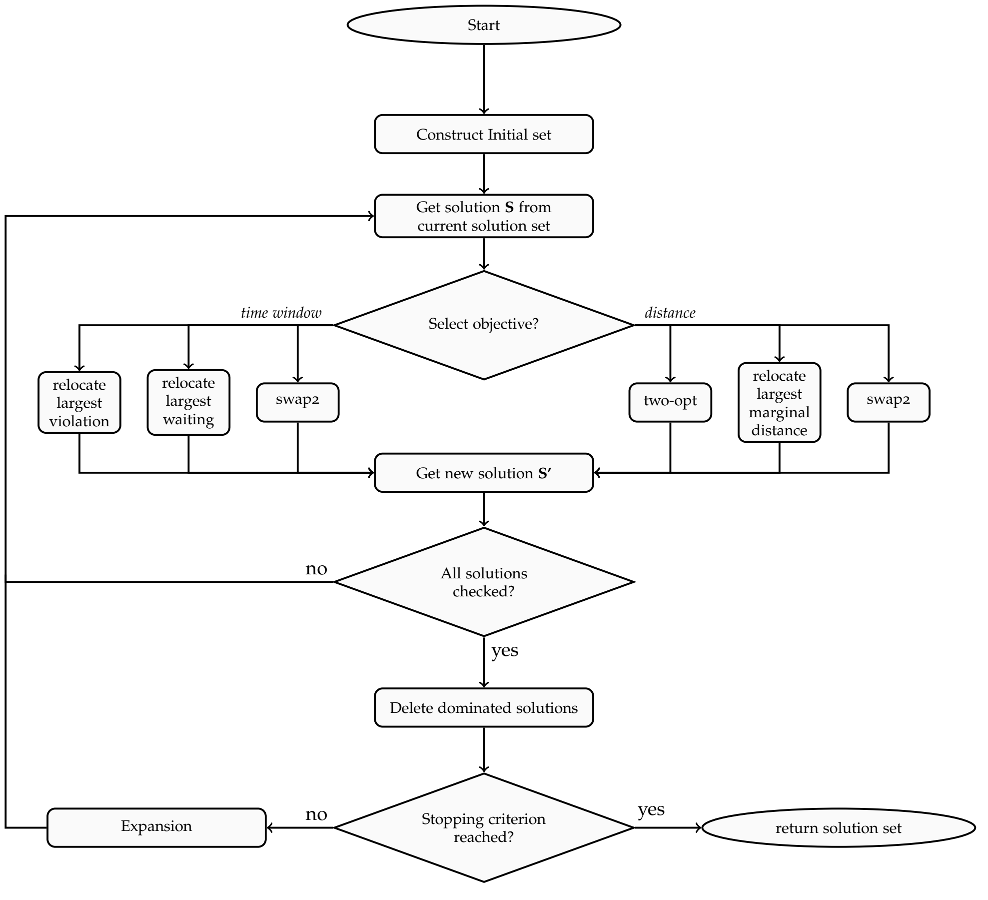


Figure 6.3: Visualisation of the developed heuristic to solve the collaborative travelling salesman problem with soft time windows at the coalition level.

6.5.2.2 *Neighbourhood structures*

To improve the current solution S, the multi-directional local search metaheuristic uses five different neighbourhoods. We refer to table 6.3 for a complete overview and a definition of all neighbourhoods. Depending on the current objective (columns *TW* and *Dist*), different neighbourhoods are available from which one is selected at random during every iteration. A first improvement search strategy is used.

Table 6.3: List of different neighbourhoods, embedded in the multi-directional VNS.

Neighbourhood	TW	Dist	Definition
RELOCATE-VIOLATION	✓		Remove the customer with the largest time window violation from the solution and insert it before the customer with the largest waiting time.
RELOCATE-WAITING	✓		Remove the customer where the vehicle has to wait the longest time from the solution and insert it after the customer for which the due time is closest to the ready time of the customer to be inserted.
RELOCATE-MARG-DIST		✓	Remove the customer with the highest marginal distance from the solution and insert it at the position where it causes a minimal insertion cost.
SWAP2	✓	✓	Swap the position of two customers in the solution.
TWO-OPT		✓	Remove two edges and replace them by two new edges to close the tour.

6.5.2.3 *Expansion*

At the end of every iteration, an *expansion operator* is called. As the current solution set represent the best pareto frontier approximation found so far, we expect that high quality solutions can be found in the close neighbourhood of the solutions in this set. By including for every solution an extra random neighbour from its *swap2* neighbourhood (see table 6.3), the number of solutions in the set is doubled. In this way, more opportunities for further improvement are created and additional *diversification* is added to the set.

6.5.3 *Step 3: Projection on the individual partner objectives*

Although all solutions returned by step 2 are coalition-efficient (the coalition as a whole is not able to further improve without worsening the value of at least one coalition objective), this does not imply that all obtained solutions are also efficient for each partner. To evaluate the Pareto-efficiency of the solutions on the partner objectives, the coalition objectives need to be redistributed to the partners.

For the time window violations this is straightforward. In order to obtain the total time window violation assigned to a partner, the violations over all customers of this partner are summed. In order to know which part of the total coalition cost should be allocated to the individual partners, a *cost allocation method* is necessary. All experimental results discussed in section 6.8 are obtained by applying the *Shapley value cost allocation method* (Shapley 1953), as it is put forward as best practice in horizontal logistics cooperations due to its desirable properties (Biermasz 2012). We also refer to section 3.3.1 for a more elaborate introduction. For more details on the implementation of the Shapley value method in the experiments, we refer to section 6.7.

6.5.4 *Step 4: Evaluation*

When projecting the obtained results on the individual partner objectives (step 3), we expect a negative correlation between the allocated cost and the corresponding time window violation for each partner. In other words, for solutions in which the partners have to tolerate a large time window violation (we say that the partner has to behave in a *flexible* way), we expect a lower cost to be allocated to this partner. This is explained by the fact that less strict time windows give rise to more efficient solutions in terms of distance (cost). On the other hand, if a partner is more rigid (and prefers solutions with smaller time window violations), we expect him to pay a higher part of the corresponding total coalition cost. This trend can also be seen in fig. 6.4, in which every point represents an efficient solution for the coalition.

Figure 6.4 shows clearly that not all solutions are on the Pareto front for the individual partner objectives (denoted by the black dots). All dominated solutions (grey) are unlikely to be accepted by the partner and are therefore disregarded. This is repeated for every partner. The solutions that is accepted by all the partner is also considered a good solution for the coalition. It is however not guaranteed that this set is non-empty.

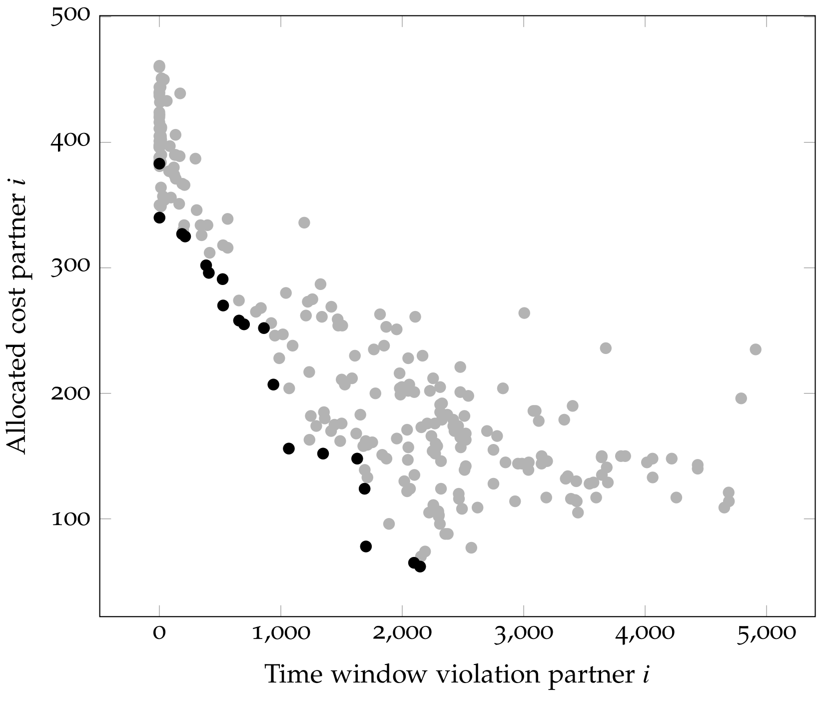


Figure 6.4: The allocated cost in function of the corresponding time window violation for one single partner in the coalition. All solutions on the Pareto frontier of the coalition are visualised by the dots. The solutions that are efficient for partner i are highlighted in black.

6.6 Partner efficiency model

The coalition efficiency method, discussed above, has some drawbacks. First of all, it requires the coalition to be able to define a global set of objectives at the coalition level. As the interests of the partners might differ significantly, this can be challenging. Furthermore, it is not guaranteed that all solutions that are efficient for all individual partners (and therefore acceptable solutions for the coalition) belong to the Pareto set of non-dominated solutions at the coalition level. In other words, a solution might be efficient for all collaborating partners, and not for the coalition. These solutions are not found by the model and algorithm discussed above. Conversely, there is no guarantee that a solution that is efficient with respect to the coalition objectives is on each of the individual Pareto fronts. In some cases, the intersection of the solutions projected onto the Pareto fronts for the individual partners might even be empty.

To overcome these issues, we propose an alternative approach that integrates the individual partner objectives directly into the optimisation procedure: the *partner efficiency model*. In the following sections, the method is presented and applied to the COLTSPSTW example.

6.6.1 *Objective functions*

For each partner, the two partner objectives (defined in section 6.4.2) are included directly into the objective function. As the cost of a solution is determined by a cost allocation method, this method should be *integrated in the objective function of the solution procedure for the operational planning itself*.

Solutions will only be retained when they are efficient for every partner. However, it is likely that solutions with a lower total distance (cost) or time window violation are beneficial for at least one (in best-case: most) of the partners. Therefore, these objectives are also added to the model. Although only the individual partner objectives are used to evaluate the current solutions, these additional objectives might guide the search towards the more interesting parts of the solution space. In this way, we try to reduce calculation time by avoiding the exploration of solutions that are far from optimal.

To summarise, four different types of objective functions can be identified in our model formulation (see also table 6.4): the minimisation of the time window violations for partner i (TW_i), the minimisation of the cost allocated to partner i ($Cost_i$), the minimisation of the total time window violation (TW) and the minimisation of the total distance driven ($Dist$). Compared to the coalition efficiency model, the number of objectives in the partner efficiency model will be high. This high dimensionality is expected to increase the complexity of the model significantly.

6.6.2 *Metaheuristic solution approach*

Similar to the coalition efficiency model, a multi-directional local search metaheuristic is used to tackle the multi-objective COLTSPSTW. To allow as much as possible a fair comparison of the two approaches, an attempt was made to maximize the similarity between both metaheuristics. Although the basic structure of the algorithm remains unaltered, a different approach is required at some points during the search. We will highlight these differences in the following sections.

6.6.2.1 *Neighbourhood structures*

Our metaheuristic makes use of six local search neighbourhoods to handle the four different types of objective functions in the model. Some of these neighbourhoods are constructed for one specific objective (e.g., the RELOCATE-VIOLATION neighbourhood focuses on time window violation minimisation) while others are more general (e.g., SWAP2 and RELOCATE). For a complete overview, we refer to table 6.4.

6.6.2.2 *Solution evaluation*

To evaluate a candidate neighbour solution with respect to the individual partner objectives, the projection on the individual partner objectives of the time window violations and the total cost should be calculated. This means that n two-dimensional Pareto fronts (such as the graph shown in fig. 6.4) should be maintained during the search for an n-partner coalition.

Table 6.4: List of different neighbourhoods, embedded in the multi-directional VNS.

Neighbourhood	TW_i	$Cost_i$	TW	Dist	Definition
RELOCATE-VIOLATION	✓		✓		Remove the customer with the largest time window violation from the solution, and insert it before the customer with the largest waiting time.
RELOCATE-WAITING	✓		✓		Remove the customer where the vehicle has to wait the longest time from the solution, and insert it after the customer for which the due time is closest to the ready time of the customer to be inserted.
RELOCATE-MARG-DIST				✓	Remove the customer with the highest marginal distance from the solution, and insert it at the position where it causes a minimal insertion cost.
RELOCATE	✓	✓			Remove one customer from the solution, and insert it again in the solution at the position where it improves the current objective the most.
SWAP2	✓	✓	✓	✓	Swap the position of two customers in the solution.
TWO-OPT		✓		✓	Remove two edges and replace them by two new edges to close the tour.

While running the optimisation procedure, we make use of a *weak domination rule*. This rule states that every solution that is part of the current Pareto frontier of at least one partner, is kept in the solution set. In this way we allow the algorithm to improve the solution further for the other partners during the following iterations.

A *strong domination rule* is used in two situations: when (i) the stopping criterion is reached and if (ii) the total number of solutions in the pool reaches a predefined threshold value. As in each iteration, the algorithm searches all solutions–objective combinations, this last rule should prevent the algorithm from taking all available calculation time for executing a limited number of iterations. The strong domination rule disregards all solutions that are not in the intersection of all individual Pareto frontiers and, consequently, only solution that are efficient for *all* partners in the coalition are kept.

6.7 Algorithmic implementation of the Shapley value

6.7.1 *Definition*

In both model described in this chapter, a cost allocation method is assumed to be selected by the collaborating partners to properly divide the total coalition cost. In our computational experiments, we chose the *Shapley value cost allocation method* based based on the Shapley value as defined by Shapley (1953).

The result of this game theoretical approach is determined by playing a cooperative game (N, C), where N represents the coalition with n collaborating players (partners), and C the *characteristic function* (Zolezzi and Rudnick 2002). This characteristic function is defined by the cost of *all possible subcoalitions* S, with $S \subset N$. The cost allocated to partner i, denoted by x_i, is now defined according to the following formula.

$$\psi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!(|N| - |S| - 1)!}{|N|!}(c(S \cup i) - c(S))$$

We also refer to section 3.3.1 of this dissertation.

6.7.2 *Algorithmic implementation*

The characteristic function requires the total coalition cost for every subcoalition $S \subseteq N$ to be known. However, the solution set for a subcoalition is represented by a Pareto front in which each solution has a different total cost. Therefore, obtaining *the* cost for a subcoalition is not straightforward. To allow a fair comparison of the cost of two solutions from different subcoalitions, we introduce the idea of *constant flexibility*. This idea assumes that the attitude of a partner towards flexible behaviour is independent of the coalition configuration.

Consider the following example for a two-partner coalition. The collaborative solution for which we want to allocate the total cost induces a time window violation of 200 and 500 for the partners respectively. To calculate the Shapley value, the stand-alone cost of each partner should be known. As the stand-alone scenario of each individual partner is represented by a Pareto front, the cost from the stand-alone

Table 6.5: Binary-to-integer conversion of all subcoalitions for a three-partner coalition.

integer	binary	integer	binary
1	0 0 1	5	1 0 1
2	0 1 0	6	1 1 0
3	0 1 1	7	1 1 1
4	1 0 0		

solution that corresponds to a time window violation of 200 is taken for partner 1. A similar approach is used to determine the stand-alone cost of partner 2. In this way, it is assured that the difference in cost for the two solutions are based solely on the difference in coalition configuration as the values on the time window violation objective are equal.

To include the Shapley value in the partner efficiency model, an *integer–to–binary conversion* is used. Each subcoalition is labelled by an integer ranging from 1 up to $2^n - 1$, for an n-partner cooperation. The composition of a subcoalition (stating if a partner is a member of this subcoalition or not) is obtained by the corresponding binary representation. For a three-partner coalition, the different subcoalitions are simulated in the order shown in table 6.5. In this way it is ensured that all (sub)coalitions can rely on the results of their subcoalitions.

6.8 Computational experiments

Both methods and their underlying algorithmic solution approaches, previously discussed in this chapter, are implemented in C++ (MS visual studio) and tested on existing benchmark instances, found in the TSPSTW literature. All computational results are obtained using an Intel(R) Core(TM) i7-4790 @ 3.60GHz and 16GB of RAM (Linux operating system with wine interface).

6.8.1 *Benchmark instances*

For the experiments, we used the benchmark instances provided by Dumas et al. (1995) as the input for all the stand-alone scenarios, i.e., for every partner in the coalition, another benchmark instance is selected. A coalition of multiple partners is therefore represented by a *combination of multiple existing benchmark instances*. In order to prevent the aggregated instances from becoming too large to solve them in a reasonable amount of time, we limit the experiments to the small instances with 20 client nodes. The aggregated three-partner instances therefore contain 60 customer nodes and eight objectives from which two at the coalition level and two for each individual partner. Four different coalitions are simulated, based on the combination of instances shown in table 6.6. The instance are named as follows: *n[number-of-customers]w[time-window-width].[id-number].txt*.

Table 6.6: Construction of the benchmark instances.

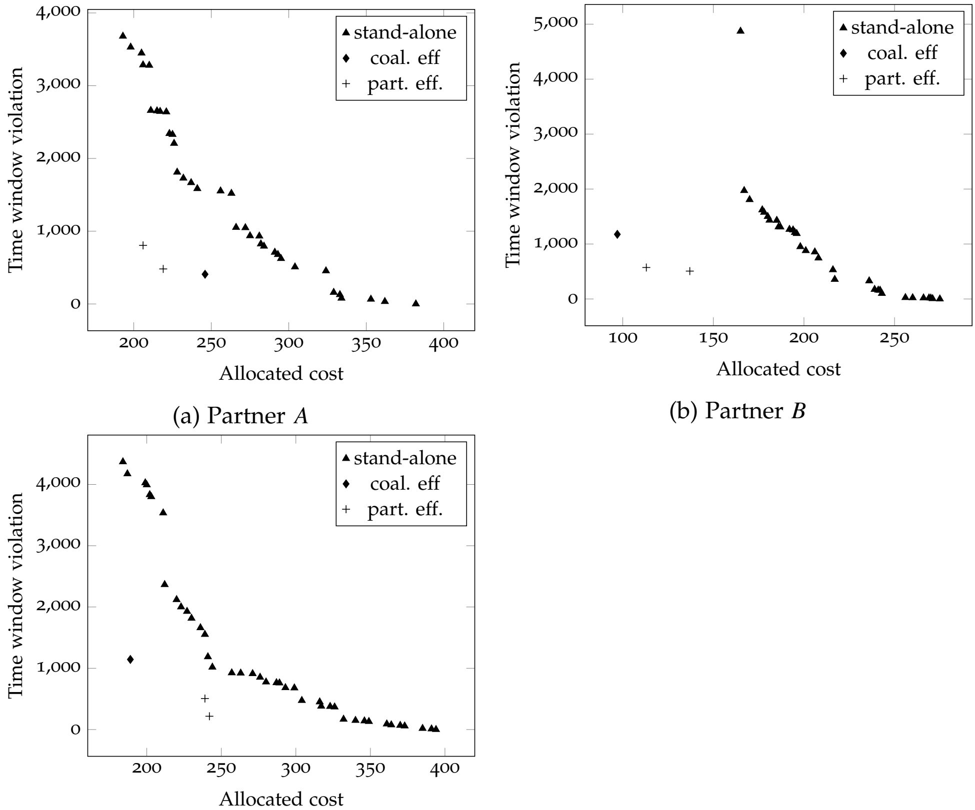
Coalition id	**Partner A**	**Partner B**	**Partner C**
C1	n20w20.001.txt	n20w20.002.txt	n20w20.003.txt
C2	n20w40.001.txt	n20w40.002.txt	n20w40.003.txt
C3	n20w60.001.txt	n20w60.002.txt	n20w60.003.txt
C4	n20w80.001.txt	n20w80.002.txt	n20w80.003.txt

6.8.2 *Stopping criterion*

To allow a fair comparison between the two methods and the results obtained for subcoalitions of different sizes, we will use a predefined number of iterations as the stopping criterion. In each iteration, we try to improve every solution in the current Pareto set with respect to every objective function in the model. In other words, a new iteration is initiated every time the expansion operator is called. The required calculation time will therefore vary significantly according to the model complexity and the instance size. In what follows, the maximal number of iterations is set to 100.

6.8.3 *Simulation results*

The set of three-partner coalitions is solved by applying both the coalition efficiency model and the partner efficiency model. All obtained results are visualised in figs. 6.5 to 6.8 and summarised in table 6.7. In all figures, the stand-alone scenario is obtained by solving the (non-collaborative) travelling salesman problem with soft time windows for each individual partner separately (see also section 6.4.1). The main conclusions are discussed in this section.



(a) Partner A

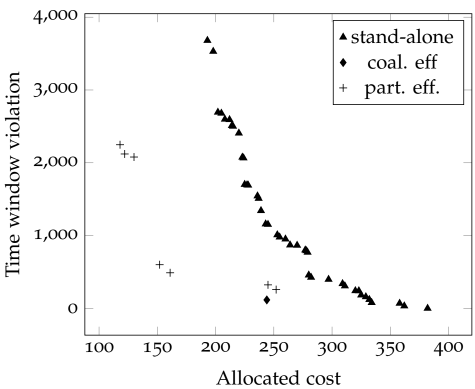
(b) Partner B

(c) Partner C

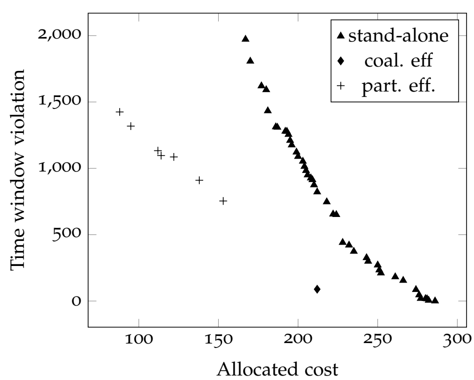
Figure 6.5: Solutions for the C1 instance.

First, we can conclude that engaging in a horizontal cooperation is profitable for all partners in the simulated coalitions. All solutions returned by both the coalition efficiency model and the partner efficiency model dominate the stand-alone solutions. This means that a reduction in both total cost and time window violation is realised for all partners through horizontal cooperation.

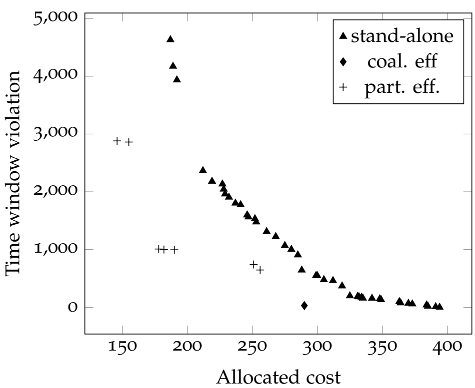
Furthermore, in table 6.7, the number of coalition efficient solutions found in step 2 of the coalition efficiency model is given in column '#CE-sol'. From this set, the number of solutions on the efficient Pareto front of all partners is given in column '#sol'. It can be concluded that a feasible solution is found for three out of four simulated coalitions. For coalition C4, none of the coalition-efficient solutions was non-dominated with respect to all individual partner objectives. Compared to the



(a) Partner *A*



(b) Partner *B*



(c) Partner *C*

Figure 6.6: Solutions for the C2 instance.

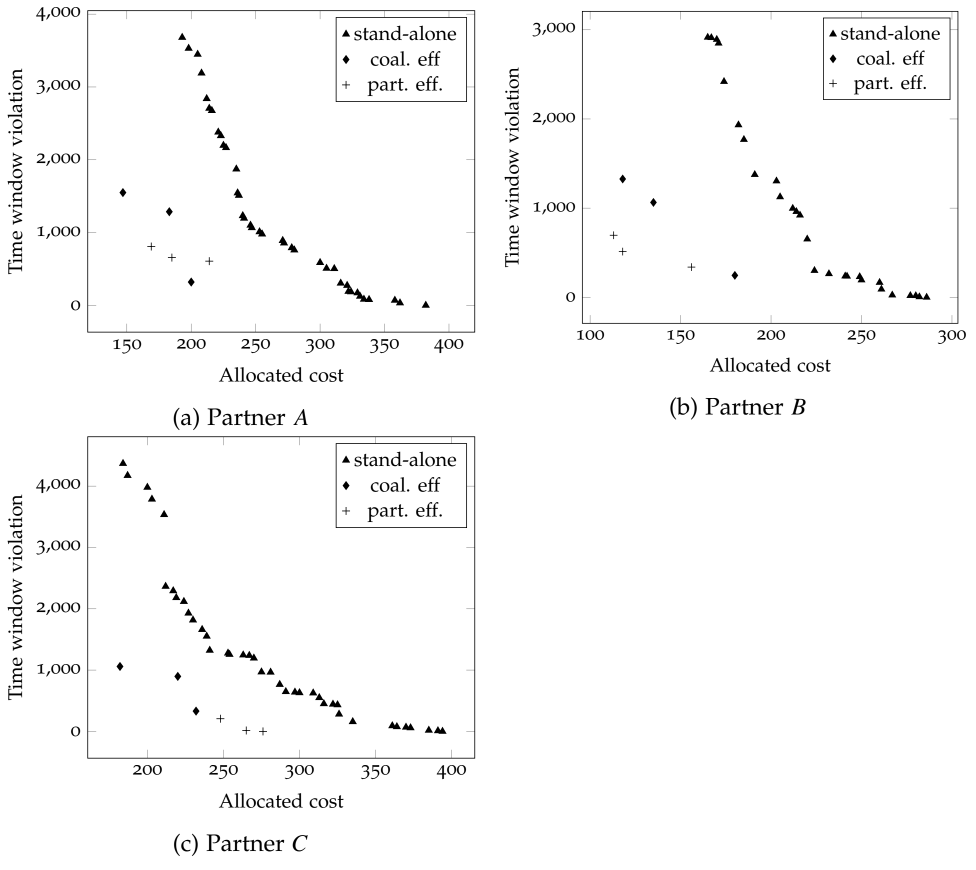
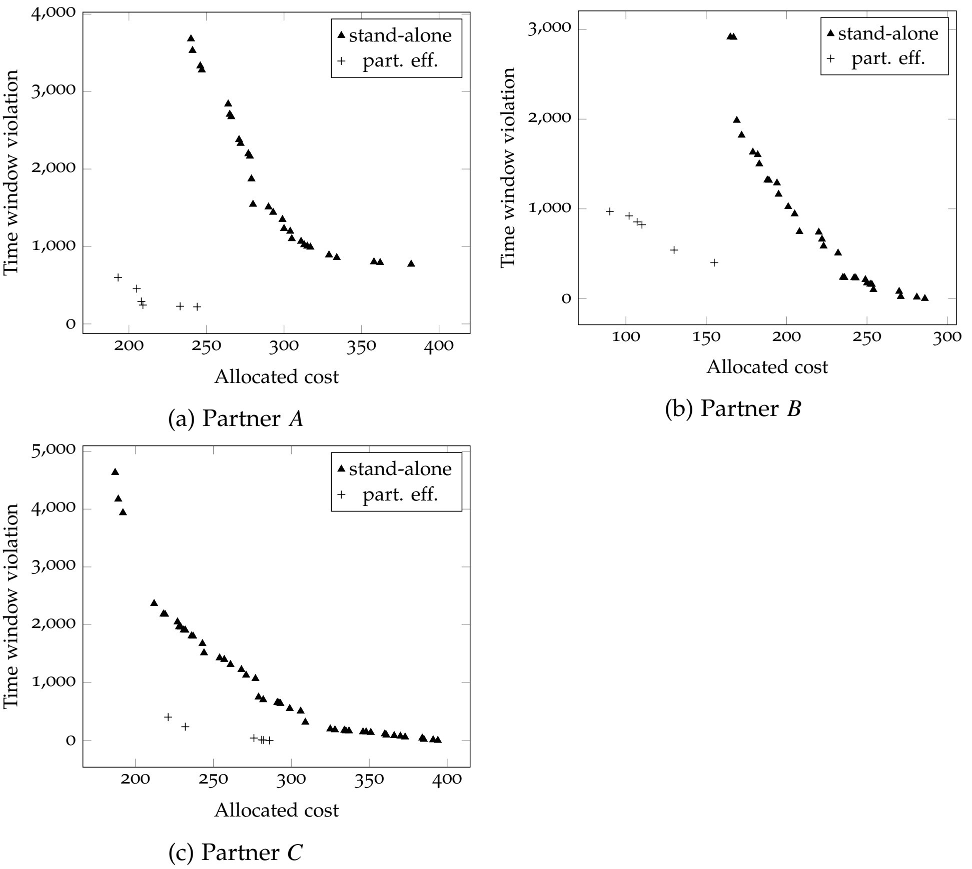


Figure 6.7: Solutions for the C3 instance.



(a) Partner *A*

(b) Partner *B*

(c) Partner *C*

Figure 6.8: Solutions for the C4 instance.

partner efficiency model, only a limited number of solutions is returned by the coalition efficiency model.

Table 6.7: Overview of all simulation results for 100 iterations.

	Coalition efficiency model					**Partner efficiency model**			
	Calculation time (s)			**Results**		**Calculation time (s)**			**Results**
	1 partner	**2 partners**	**3 partners**	**#CE-sol**	**#sol**	**1 partner**	**2 partners**	**3 partners**	**#sol**
C1	1.09	6.40	25.02	92	1	2.71	185.71	1777.86	2
C2	1.04	7.52	29.22	97	1	3.04	190.30	990.43	7
C3	0.95	7.38	29.72	56	3	2.90	172.81	1761.75	3
C4	0.96	7.37	25.64	95	0	3.06	202.66	2288.37	6
average	1.01	7.17	27.40			2.93	187.87	1704.60	

This might be due to the fact that the model's main objective is the *efficiency of the coalition*. Solutions are therefore only constructed according to the objectives defined at the coalition level. It is after the optimisation, in steps 3 and 4, that the obtained solutions are evaluated by the individual partners and removed if not efficient. It should be acknowledged that finding a good intersection for all individual partners' objectives during the evaluation phase is a matter of luck, as these individual objectives are not taken into account while constructing the solution set at the coalition level. Therefore, there might exist a large discrepancy between the direction in which the optimisation is executed (coalition objectives), and the way the final solutions are evaluated (individual partner objectives). Furthermore, the Shapley value cost allocation mechanism relies on the solution set found for *every possible subcoalition of the coalition*, which therefore has to be simulated as well. A small change in one of these subcoalition Pareto frontiers might result in a different evaluation of the current solutions at the coalition level.

The partner efficiency model tends to provide a better approximation of the underlying Pareto frontiers. The reason is twofold. First, by not limiting the search to only solutions that are Pareto-efficient at the coalition level, additional solutions are found in the partner efficiency model that will never be considered by the coalition efficiency model. Second, the optimisation problem is solved directly at the individual partner level, without introducing the aggregation step towards the coalition level. As a result, the evaluation potential solutions is in line with the optimisation procedure itself. The partner efficiency model is therefore able to provide the decision maker with a more complete view on the trade off between the different individual partners' objectives. This strength is also its biggest drawback as due to the growing number of objectives, the computational complexity of the model increases significantly, resulting in larger calculation times. The average calculation time for all subcoalitions of different sizes are also shown in table 6.7.

6.9 Conclusions and future research

The recent trend of horizontal cooperation in logistics receives increasing attention as it can yield some major advantages. Because of a more efficient operational planning, transportation companies are able to reduce the total logistics cost, while maintaining high service levels. From an operational perspective, however, horizontal cooperation requires existing models to be revised in order to comply with a multi-partner collaborative environment. This chapter can be considered as a first, exploratory step towards more integrated methods for operational optimisation in a multi-partner context.

In this chapter, we introduced the concepts of *coalition efficiency* and *partner efficiency* to acknowledge a difference in priorities and goals between all collaborating partners, and between the group and the individual players. We have used these definitions to construct two new solution approaches for solving a multi-objective collaborative transportation problem: the *coalition efficiency model* and the *partner efficiency model*. Both models aim at providing the decision makers with a solution set by focusing not only on the performance of the group but also on the individual objectives of each partner.

To ensure that the total coalition cost is divided properly among all collaborating partners, both models aim at integrating a cost allocation mechanism into the optimisation procedure. In the coalition efficiency model, this is done sequentially after an aggregated logistics plan is constructed for the coalition as a whole. The partner efficiency model on the other hand, combines the operational planning and the cost allocation method into one optimisation problem. Although this integration might guide the search into a more desirable direction during the optimisation phase, it will increase the complexity of the model exponentially.

The coalition efficiency model is able to generate good quality solutions in relatively short calculation times. However, due to the fact that the optimisation is executed at coalition level where as afterwards solutions are evaluated on the partner level objectives, only a very limited number of solutions is returned by the algorithm. The fact that an efficient solution at the coalition level is also efficient at individual partner level can be considered a matter of “luck”. The partner efficiency model, on the other hand, provides the decision maker with a more complete Pareto front approximation, allowing a better understanding of the underlying trade-offs between the different objectives of the individual partners. Because of this reason, we prefer the partner efficiency model as all individual partner objectives are included explicitly in the optimisation procedure. This is, however, at the expense of very high calculation times, compared to the coalition efficiency model.

As both models possess advantageous properties, a promising opportunity for further study would be the integration of both ideas. The aim of that integrated model should be finding a balance between the objectives at coalition and partner level. The integration of both models is considered in chapter 8.

Furthermore, we aim to integrate different cost allocation methods into the suggested models and study the impact of these methods on the obtained solution set (the form of the obtained Pareto frontier). Also, the integration of more qualitative techniques for the evaluation and comparison of multi-objective solution spaces (e.g., the hypervolume, measures of spacing and spread,. . .) might improve the overall quality of the solution implementation for both models.

7

The Clustered vehicle routing problem

Abstract:

In this chapter, we present an improved two-level heuristic to solve the Clustered Vehicle Routing Problem (CLUVRP). The CLUVRP is a generalization of the classical (Capacitated Vehicle Routing Problem (CVRP)) in which customers are grouped into predefined clusters, and all customers in a cluster must be served consecutively by the same vehicle. This chapter contributes to the literature in the following ways: (i) new upper bounds are presented for multiple benchmark instances, (ii) good heuristic solutions are provided in much smaller computing times than existing approaches, (iii) the CLUVRP is reduced to its cluster level without assuming Euclidean coordinates or distances, and (iv) a new variant of the CLUVRP, the CLUVRP with weak cluster constraints*, is introduced. In this variant, clusters are allocated to vehicles in their entirety, but all corresponding customers can be visited by the vehicle in any order.*

The proposed heuristic solves the CLUVRP by combining two variable neighbourhood search algorithms, that explore the solution space at the cluster level and the individual customer level respectively. The algorithm is tested on different benchmark instances from the literature with up to 484 nodes, obtaining high quality solutions while requiring only a limited calculation time.

7.1 Research context and literature review

Introduced by Dantzig and Ramser (1959), the vehicle routing problem (VRP) is one of the best known and most widely studied problems in the Operations Research community. Many variants of the VRP have been proposed and solved during the last decades. In this chapter, we focus on the *clustered vehicle routing problem* (CLUVRP), a variant of the capacitated vehicle routing problem (CVRP) in which all customers are partitioned into predefined *clusters*. In the *strict* version of the CLUVRP, all customers belonging to the same cluster should be visited by the same vehicle consecutively in the same path. In other words, when a customer is visited by a vehicle, all other customers belonging to the same cluster should be visited first before the vehicle can either return to the depot or move to a client that belongs to another cluster. We refer to this problem as the *clustered vehicle routing problem with strong cluster constraints*. In section 7.6, we will define a new variant of the problem with *weak cluster constraints*.

The idea of customer clustering was introduced by Chisman (1975) when defining the *clustered travelling salesman problem* (Clustered Travelling Salesman Problem (CLUTSP)). The objective of this problem is to construct a Hamiltonian path with minimum distance, visiting all customers exactly once. Customers, however, are assigned to a set of predefined clusters and an extra constraint imposes that all customers belonging to the same cluster should be served consecutively. The main algorithmic contributions regarding the CLUTSP consist of a tabu search heuristic (Laporte, Potvin, and Quilleret 1997), genetic algorithms (Ding, Cheng, and He 2007; Potvin and Guertin 1996) and a path relinking approach including GRASP (Mestria, Ochi, and Lima Martins 2013). In addition to a number of vehicle routing applications, the CLUTSP can also be applied in many other fields, such as manufacturing (machine scheduling, plate cutting, optimisation of resource usage in a production process), IT (disk fragmentation, optimisation of computer program structure) and microscopy (cytology) (Laporte and Palekar 2002).

The CLUVRP was introduced by Sevaux and Sörensen (2008) in order to model the parcel delivery activities of courier companies. A common practice in this industry is to sort all outbound parcels into bins, where each bin corresponds to a specific, predefined part of the distribution area, called a *zone*. The first step in solving the distribution planning problem of a courier company is to assign these bins (zones) to the vehicles available. A multi-objective approach for this problem is presented by Janssens et al. (2015). Afterwards, an optimal cluster and customer sequence should be determined for every vehicle. Other examples involving customer clustering can be found in situations where it is desirable that certain customers are served by the same vehicle. This might be due to the fact that some customers demand a similar service, request a specific repairman skill, or if the customer-driver relationship is perceived important by one of the parties.

In Pop, Kara, and Marc (2012), an exact method for solving the CLUVRP is developed as an extension of the Generalized Vehicle Routing Problem (Generalised Vehicle Routing Problem (GVRP)). The GVRP is closely related to the CLUVRP, as both problems share the concept of customer clustering. Contrary to the CLUVRP, the GVRP requires that only one customer is visited in every cluster (Ghiani and Improta 2000). A new compact and effective integer programming formulation and exact solution approach is proposed in Battarra, Erdoğan, and Vigo (2014).

To solve the CLUVRP heuristically, Barthélemy et al. (2010) introduce a transformation of the CLUVRP into the CVRP. This is done by adding a large distance M to all inter-cluster edges in the distance matrix. As a result, routes are obtained in which all customers of a single cluster are served before leaving the cluster, because of the high penalty costs. In Barthélemy et al. (2010) this *big M approach* is further combined with a simulated annealing heuristic.

A hybrid algorithm that does not make use of the big M transformation is proposed in Marc et al. (2015), but this algorithm uses precomputed cluster centres and is therefore only able to solve Euclidean instances. Furthermore, no calculation times are mentioned.

Two alternative metaheuristic solution approaches are proposed by Vidal et al. (2015). The first one is an adaptation of the Iterated Local Search (ILS) algorithm developed by Subramanian (2012) for the CVRP. In order to avoid the evaluation of many infeasible moves, due to the additional cluster constraints, the neighbourhoods are redefined. Secondly, Vidal et al. (2015) use their Unified Hybrid Genetic Search (UHGS) approach to solve the CLUVRP. Since this method is designed to solve the non-clustered VRP, the pre-computation of all intra cluster Hamiltonian paths is required. The authors report high quality solutions for both methods. This solution quality, however, comes at the expense of very high calculation times.

Defryn and Sörensen (2015c) propose a decomposition of the problem in two optimisation levels: a high-level routing problem at the cluster level and a low-level routing problem at the individual customer level. Expósito-Izquierdo, Rossi, and Sevaux (2016) acknowledge the two-level optimisation strategy and propose a solution algorithm that combines the Record-to-record algorithm (Li, Golden, and Wasil 2007) at the cluster level with the Lin-Kernighan heuristic (Lin and Kernighan 1973) to determine the intra-cluster routes.

The current chapter contributes to the existing literature in the following ways. First, we are able to report improved results on most of the instances provided by Expósito-Izquierdo, Rossi, and Sevaux (2016). Secondly, even though good algorithms exist for solving the CLUVRP , most notably the ones proposed by Vidal et al. (2015), a gap remains for an approach that allows to calculate good solutions in a *short amount of computing time*. The heuristic procedure proposed in this chapter is able to generate good quality feasible solutions very fast. Such an algorithm is necessary in situations where large calculation times are not available or impractical, such as in the daily planning process of couriers or other transportation companies. It is additionally useful in applications for which the CLUVRP is solved many times as a subproblem. For example, the problem of defining the optimal customer clusters in the distribution area will rely on the CLUVRP solution as an evaluation criterion. In this case, a fast evaluation is preferred over the fact that the optimal solution is guaranteed. A third contribution is that, compared to Defryn and Sörensen (2015c) and Expósito-Izquierdo, Rossi, and Sevaux (2016), we generalise the two-level framework to also handle non-Euclidean instances. Finally, a new CLUVRP variant, i.e., the CLUVRP *with weak cluster constraints* is introduced in this chapter. For some applications, the use of clusters might be beneficial to some extent (e.g., the sorting of the packages and the allocation of zones to vehicles for courier companies, as described above), but could be relaxed when it comes to optimising the route of a single vehicle. In other words, the CLUVRP with *weak* cluster constraints still enforces that all customers belonging to the same cluster are visited by the same vehicle, but relaxes the constraint that they should be visited *consecutively*. The customers in the clusters assigned to a vehicle therefore can be visited in any order. To the best of our knowledge, this problem has not yet been described in the literature.

The structure of the chapter is as follows. In section 7.2, the CLUVRP is formally described, after which a detailed analysis of the developed metaheuristic is performed in section 7.3. Our algorithm is tuned and tested on multiple instances of different sizes in sections 7.4 and 7.5. The CLUVRP with weak cluster constraints is introduced and compared to the original strong cluster constraint variant in section 7.6. Finally, the main conclusions are summarised in section 7.7.

7.2 Problem definition

In the CLUVRP with strong cluster constraints, we are given a complete undirected graph $G = (V, E)$, where V is a set of vertices including one depot (denoted as V_0) and multiple customer nodes. A distance d_{ij}, is associated with each edge $(i, j) \in E$ connecting two nodes. We consider K to be a set of homogeneous vehicles with a maximum capacity Q each. All vehicles start and end their trip at the depot. For each customer i the demand is denoted by q_i. Furthermore, a set of clusters is denoted by R. Cluster $r_0 \in R$ only contains one node, the depot. All other clusters contain at least one customer. The set of customers in a cluster is denoted as $C_r = \{i \in V \backslash V_0 : r_i = r\}$, $\forall r \in R$.

Following Expósito-Izquierdo, Rossi, and Sevaux (2016), the CLUVRP can be defined by the mathematical model described below. Consider Z to be any proper subset of V. Then, let $\delta^+(Z)$ be the set of edges $(i, j) \in Z \times V \backslash Z$ (i.e., the edges connecting all vertices in Z with the vertices not in Z, referred to as outgoing edges) and $\delta^-(Z)$ the set of edges $(i, j) \in V \backslash Z \times Z$ (i.e., the edges connecting all vertices outside of Z with all vertices in Z, referred to as incoming edges).

$$x_{ijk} = \begin{cases} 1 & \textit{vehicle } k \textit{ travels from node } i \textit{ to node } j \\ 0 & \textit{otherwise} \end{cases}$$

$$y_{ik} = \begin{cases} 1 & \textit{customer } i \textit{ is served by vehicle } k \\ 0 & \textit{otherwise} \end{cases}$$

$$\min \sum_{(i,j)\in E} \sum_{k\in K} d_{ij} x_{ijk} \tag{7.1}$$

Subject to

$$\sum_{k\in K} y_{ik} = 1 \qquad \forall i \in V \backslash V_0 \tag{7.2}$$

$$\sum_{k\in K} y_{0k} = |K| \tag{7.3}$$

$$\sum_{j\in V\backslash V_0} x_{ijk} = \sum_{j\in V\backslash V_0} x_{jik} = y_{ik} \qquad \forall k \in K, \forall i \in V \tag{7.4}$$

$$\sum_{i\in V} q_i y_{ik} \leq Q \qquad \forall k \in K \tag{7.5}$$

$$\sum_{i\in S} \sum_{j\notin S} x_{ijk} \leq y_{hk} \qquad \forall Z \subseteq V \backslash V_0, \forall h \in Z, \forall k \in K \tag{7.6}$$

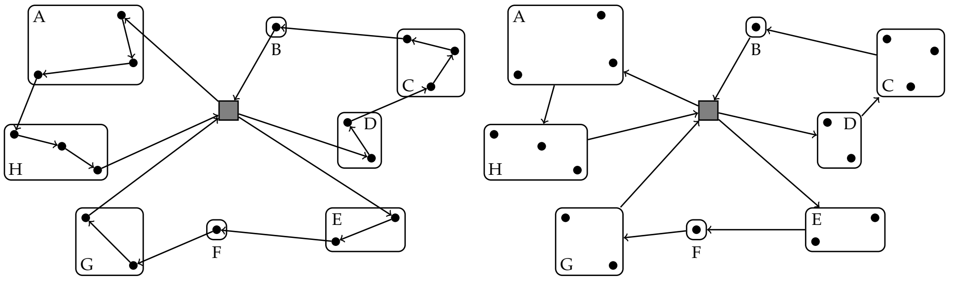
$$\sum_{(i,j)\in\delta^+(C_r)} \sum_{k\in K} x_{ijk} = \sum_{(i,j)\in\delta^-(C_r)} \sum_{k\in K} x_{ijk} = 1 \qquad \forall r \in R \tag{7.7}$$

$$x_{ijk} \in \{0,1\} \qquad \forall (i,j) \in E, \forall k \in K \tag{7.8}$$

$$y_i \in \{0,1\} \qquad \forall i \in V, \forall k \in K \tag{7.9}$$

In the model formulation above, the objective function (eq. (7.1)) minimises the total distance travelled by all vehicles. Equation (7.2) ensure that each customer is visited exactly once. Equation (7.3) state that all vehicles should visit the depot. Equation (7.4) guarantee that the same vehicle that arrives at a customer also leaves from that customer. Equation (7.5) make sure that vehicle capacities are respected. The subtour elimination constraints are represented by eq. (7.6). Equation (7.7) establish that each cluster is visited exactly once by one vehicle (e.i., there is exactly one incoming and one outgoing edge for the cluster r).

The CLUVRP is visualised in fig. 7.1. On the left hand side, the final solution of the CLUVRP with strong cluster constraints is shown at the individual customer level. The corresponding solution at the cluster level is included at the right hand side. This high level representation will be used during the algorithm to reduce the complexity of the problem by exploiting its clustered substructure.



(a) A CLUVRP solution at the customer level (b) A CLUVRP solution at the cluster level

Figure 7.1: The CLUVRP with strong cluster constraints.

As demonstrated by Lenstra and Kan (1981), the CVRP is NP-hard. Since any CVRP can be reduced to a CLUVRP with one customer in each cluster and the complexity of this reduction is linear with respect to the number of customers, the CLUVRP is also NP-hard (Barthélemy 2012).

7.3 A metaheuristic approach for the CLUVRP

We propose a metaheuristic approach that explores the solution space at two different levels: the *cluster level* and the *customer level*. At both levels, a Variable Neighbourhood Search (VNS) algorithm is used to find a local optimum. VNS, introduced by Mladenović and Hansen (1997) has proven to be a successful framework for solving combinatorial optimisation problems, especially vehicle routing problems (Hansen and Mladenović 2014). First, the problem is solved at the cluster level. Afterwards, this result is used as an input for the customer level VNS. During the diversification phase, the algorithm moves back from the customer to the cluster level. The outline of our heuristic is shown in algorithm 2. In the following sections, we take a closer look at the different operators and their implementation.

Algorithm 2 Pseudocode of the two-level metaheuristic approach for solving the CLUVRP.

```
nIterationsNoImprovement ← 0;
goToNodeVNS ← false; stoppingCriterion ← false;
best solution found: S_i^*;
objective value of best solution found: f(S_i^*) ← ∞ ;
Step 0: Precomputation
calculate-inter-cluster-distances();
Step 1: Constructive phase
S_c ← allocate-clusters-to-vehicle();
Step 2: Intensification phase
do
    S_c' ← perform-VNS-at-cluster-level(S_c);
    do
        S_i ← convert-from-cluster-to-customer-level(S_c');
        S_i' ← perform-VNS-at-customer-level(S_i);
        if f(S_i') < f(S_i^*) then
            S_i^* ← S_i';
            f(S_i^*) ← f(S_i');
            nIterationsNoImprovement ← 0;
        else
            nIterationsNoImprovement ← nIterationsNoImprovement + 1;
            if nIterationsNoImprovement = maxIterationsNoImprovement then
                stoppingCriterion ← true;
                break;
            end if
        end if
        Step 3: Diversification phase
        S_c ← perturb(S_c');
        repair(S_c);
        r ← get-random-number[0,1]();
        if r < cluVNSProb then
            goToNodeVNS ← false;
        else
            goToNodeVNS ← true;
        end if
    while goToNodeVNS = true;
while stoppingCriterion = false;
return S_i^*;
```

7.3.1 *Precomputation*

During precomputation all inter cluster distances are quantified. As described earlier, only the distance $d_N(i, j)$ between individual nodes i and j is given. These distances are not necessarily symmetrical or Euclidean. To solve the CLUVRP at the cluster level (i.e., to determine the assignment of clusters to vehicles and the sequencing of the clusters per vehicle), the *inter cluster distance matrix* should be defined. For this purpose we use the shortest edge between two clusters as an approximation for the inter-cluster distance as this will be the preferred edge to go from one cluster to another in the low-level routing solution.

7.3.2 *Constructive phase*

The main goal of the constructive phase is to generate a feasible initial solution at the *cluster level*. This means that for every cluster, the individual customers are disregarded and the cluster as a whole is allocated to an available vehicle. Even though the travel times between the clusters are taken into account during the constructive process, constructing a feasible allocation of clusters to vehicles is the priority in this phase. Therefore, instead of using a VRP algorithm, a *bin packing approach* is preferred here. This design choice is justified as follows.

First, contrary to a standard VRP formulation, the number of vehicles is given and should not be optimised any further, as all vehicles must be used anyway. As a result, the exact number of trips is known in advance. Furthermore, it can be argued that the inter cluster Hausdorff distances are only an approximation of the distances between two clusters, as the real distance depends on both the cluster and customer sequence in the trip. Finally, the instances (especially the smaller ones) are constructed in such a way that only very little to no spare capacity is available. For these reasons, a problem specific bin packing approach is more suitable here.

If we disregard the travel of the vehicles between clusters, the allocation of clusters with their given demand to a set of vehicle can be modelled as a *one-dimensional bin packing problem with given number of bins*. A set of items (clusters) with a given weight (total demand) are to be packed into a set of bins (vehicles) with a predefined maximal load (vehicle capacity Q).

The one-dimensional bin packing problem is shown to be strongly NP-complete (Garey and Johnson 1978). Because we are not interested in the optimal bin packing solution, but a solution for the CLUVRP, we prefer a fast algorithm that provides us with a feasible result. The *first-fit decreasing* and the *best-fit decreasing* algorithms are most commonly applied in the literature. In this chapter, the best-fit decreasing strategy is adopted.

The traditional best-fit bin packing algorithm places each item (cluster), in succession, into the fullest bin (vehicle) in which it fits (Fleszar and Hindi 2002). For a simple bin packing problem this is satisfactory, but when solving the CLUVRP, it is important that efficient routes can be constructed afterwards with the clusters that have been allocated to the same vehicle. For every cluster, sorted in decreasing order according to demand, we therefore look at the latest cluster that was added to all the bins (vehicles). We then prefer the vehicle for which this latest cluster is located the closest to the current cluster to add. In this way, the algorithm is more likely to combine different clusters that are located in the same part of the distribution area into one vehicle. Once a vehicle has departed from the depot in a certain direction (certain clusters are assigned to that vehicle), we force that other clusters in that same direction are also allocated to this vehicle.

Due to the deterministic character of this constructive heuristic, the same initial solution will be generated during every run of the algorithm. In order to prevent this from happening, an alternative strategy, which involves some randomness, is defined. With a predefined probability RANDCONSTRUCTPROB, the current cluster is not allocated to the closest vehicle, but from all feasible vehicles (vehicles with enough spare capacity) one vehicle is selected at random.

7.3.3 *Redistribution algorithm*

As for each instance the number of vehicles is given, the heuristic constructive procedure used to allocate clusters to vehicles might reach a point where no vehicle has enough capacity left to store the next cluster. In order to cope with these situations, a specific redistribution operator, that tries to re-optimize the current capacity distribution, is built into the solution algorithm.

The CLUSTERSWAP operator is illustrated in fig. 7.2. Two vehicles are considered with a capacity of 50 items each and eight clusters with a demand of $19, 14, 14, 12, 11, 11, 10$

and 7 items should be allocated to one of the vehicles. As shown, adding the last cluster to any of the vehicles will result in an infeasible solution. This issue is solved by swapping the vehicles assigned to the clusters with a demand of 14 and 10, which will result in a 100% utilisation of vehicle 2. As a results, enough spare capacity becomes available in vehicle 1 to hold the cluster with a demand of 7.

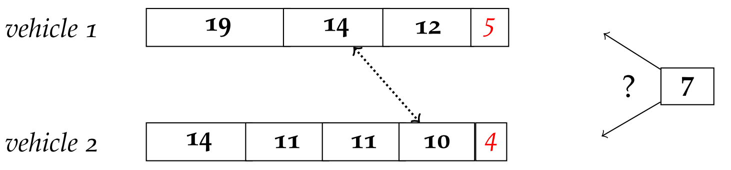


Figure 7.2: Visualisation of the clusterSwap operator.

7.3.4 *Intensification phase*

From the moment that a feasible solution is constructed, the algorithm starts the intensification phase in which the initial solution is improved until a local optimum is reached. This is done in three steps.

First, the initial solution is improved at its cluster level by means of a VNS. A locally optimal cluster sequence is obtained for every vehicle. Afterwards, this cluster level solution is translated to the individual customer level by a conversion operator. The obtained result is then used as the input for a second VNS at the individual customer level.

7.3.4.1 *Intensification at the cluster level*

The first part of the intensification phase is executed at the level of the clusters and uses the inter cluster distance matrix, constructed during precomputation. By ignoring all individual customer nodes, the problem size and complexity are reduced. The obtained high level routing problem is solved by a VNS with the objective of finding an optimal cluster sequence for every vehicle. The search is based on seven local search operators that are commonly used in vehicle routing. Both *intra and inter vehicle neighbourhoods* are explored. The intra vehicle operators try to minimize the total distance of a single trip. The inter vehicle operators combine at least two trips while trying to improve the global cost (total distance) of the solution by moving one or exchanging a set of clusters between different vehicles. All local search operators are shown in table 7.1 and have complexity $O(n^2)$. We use the *first improvement strategy*, as every beneficial move encountered is executed by the algorithm.

Table 7.1: List of all intra and inter vehicle local search operators, implemented in the VNS at the cluster level.

Intra vehicle operators	
Operator	**Definition**
SWAP	Swap the position of two clusters in a single trip.
RELOCATE	Remove one cluster and insert it at a different position in the trip.
TWO-OPT	Remove two edges and replace them by two new edges to close the tour.
OR-OPT	Remove N consecutive clusters and insert them at a different position in the trip. (with $N = \{2, 3, 4\}$)
Inter vehicle operators	
Operator	**Definition**
SWAP	Swap the vehicle of two clusters.
RELOCATE	Remove one cluster and insert it in another trip.
OR-OPT	Remove N consecutive clusters and insert them in another trip. (with $N = \{2, 3, 4\}$)

The order in which the neighbourhoods are checked by the algorithm is changed randomly each time the VNS is called. When no improvement can be found in the current neighbourhood, the algorithm moves to the next neighbourhood. Every time an improvement is found, the algorithm returns to the first neighbourhood. This is repeated until none of the neighbourhoods is able to improve the current solution any further, and a local optimum is reached at the cluster level.

7.3.4.2 *Conversion operator*

The best cluster sequence for every vehicle obtained during the intensification phase at the cluster level is converted into a solution at the customer level before sending it to the customer level intensification phase. This is done by the conversion operator.

For each cluster, an intra cluster Travelling Salesman Problem (TSP) was constructed heuristically during pre-processing. The order in which the nodes appear in this TSP is maintained by the conversion operator. The starting node is chosen as the node closest to the current position of the vehicle. In other words, when entering a new cluster, the customer that is closest to the vehicles' current position (either the last customer visited in the previous cluster of the depot) is visited first. Starting from this customer, the node sequence equals the intra cluster TSP constructed during pre-processing.

With a probability given by the parameter RANDCONVERSIONPROB, all nodes of the current clusters are added randomly to the solution. In this way, we introduce some diversification in the conversion operator and a larger part of the solution space is searched.

The solution obtained after applying the conversion operator is considered the initial solution at the customer level.

7.3.4.3 *Intensification at the customer level*

The initial solution at the customer level constructed by the conversion operator, is improved further during a second intensification phase in which all individual customer nodes are taken into account. Similar to the VNS discussed insection 7.3.4.1, a set of neighbourhoods is explored in the search for a local optimal solution.

The cluster constraints, however, impose that all customers belonging to the same cluster should remain visited consecutively in the same path. This restricts the number of feasible moves to be checked by the local search operators.

Two main groups of neighbourhoods can be distinguished: the *intra cluster* and the *inter cluster* neighbourhoods. The first group is responsible for improving the Hamiltonian path within a certain cluster. The optimality of these intra cluster routes is also dependent on the cluster sequence, as this might affect the optimal edge to enter or leave the cluster. Secondly, the inter cluster neighbourhoods operate on the cluster order as obtained by the VNS at the cluster level. As no customer information was taken into account at the cluster level, a modified cluster sequence might be beneficial. The inter cluster operators can be both intra or inter vehicle, as the performed moves can involve a single vehicle (e.g., two entire clusters swap within the same vehicle), or multiple vehicles (e.g., two entire clusters belonging to different vehicles are swapped). The neighbourhoods used by the VNS at the customer level are described in table 7.2.

Similar to the first VNS, the applied neighbourhoods are checked sequentially. When an improvement is found, the algorithm restarts by exploring the first neighbourhood. It continues until none of the neighbourhoods is able to improve the solution any further and a local optimum is reached. Again, the order in which the neigh-

Table 7.2: The different VNS neighbourhoods at the customer level.

Intra cluster operators	
Operator	**Definition**
SWAP	Swap the position of two customers within the same cluster in a single trip.
RELOCATE	Remove one customer and insert it at a different position within the same cluster.
TWO-OPT	Remove two edges and replace them by two new edges to close the tour.
OR-OPT	Remove N consecutive customers and insert them at a different position within the same cluster in the trip. (with $N = \{2, 3, 4\}$)
Inter cluster operators *(intra vehicle)*	
Operator	**Definition**
SWAP	Swap the position of two clusters within the same trip.
RELOCATE	Remove all customers of a single cluster and insert them sequentially at a different position in the same trip.
Inter cluster operators *(inter vehicle)*	
Operator	**Definition**
SWAP	Swap the vehicle of two clusters.
RELOCATE	Remove all customers of a single cluster and insert them sequentially in another trip.

bourhoods are checked by the algorithm is changed randomly by each call of the VNS.

7.3.5 *Diversification phase*

After having evaluated the new solution obtained at the customer level, the algorithm executes its diversification strategy to continue the search and explore another part of the solution space. This diversification operator consists of a *perturbation operator*, that destroys parts of the solution, followed by a *repair operator*.

As all customer nodes that belong to the same cluster should remain grouped together, the removal of one customer node by the perturbation operator would in the end result in the removal of the complete cluster this customer belongs to. Therefore, the perturbation operator is applied immediately to the current solution at the cluster level. A random part of the solution, denoted by the parameter PERTRATE, is destroyed and the removed clusters are stacked in a separate list.

Afterwards, all removed clusters are reallocated to random vehicles by the repair operator while making sure that the vehicle capacity constraints are not violated. If no feasible vehicle can be found for a certain cluster, the redistribution operator (described in section 7.3.3) is called by the algorithm.

When a new solution is obtained, the algorithm can resume its search at two different points. Either the new solution at the cluster level is improved first by the intensification phase at the cluster level, or the algorithm calls the conversion operator immediately after the diversification phase. The probability to call the VNS at the cluster level after the diversification operator is denoted by the parameter CLUVNSPROB.

7.4 Parameter tuning and stopping criterion

7.4.1 *Parameter tuning*

The algorithm is controlled by four parameters, summarised in table 7.3. In order to fully test the impact of these parameter values on the solution quality, a full factorial statistical experiment is executed. The tuning is done on a selection of large-size instances as provided by Battarra, Erdoğan, and Vigo (2014). See section 7.5 for a more elaborate presentation of the instances. The results of this tuning procedure are visualised in fig. 7.3, for each individual parameter. The obtained best parameter settings are shown in the last column of table 7.3. The optimal value for the RANDCONSTRUCTPROB parameter is zero, stating that allocating each cluster to a close-by vehicle outperforms a randomized approach. For the CLUVNSPROB parameter, the optimal value equals 1, meaning that after the diversification phase the best strategy is again to first optimise the solution at the cluster level. All results in this chapter are obtained using these optimal parameter values.

Table 7.3: Results of parameter tuning on a small subset of the large-size instances.

Parameter	Definition	Tested Values	#	Best
RANDCONSTRUCTPROB	Probability that a cluster is allocated to a random instead of the closest feasible vehicle during construction.	0,0.1,...,0.5	6	**0**
RANDCONVERSIONPROB	Probability that an intra cluster route is inserted randomly instead of using the nearest neighbour approach.	0,0.1,...,1	11	**0.4**
PERTRATE	Percentage of the solution that is randomly destroyed by the perturbation operator.	0,0.1,...,0.5	6	**0.1**
CLUVNSPROB	Probability that, after the diversification phase, the new solution is improved first at the cluster level before going to the conversion operator.	0.2,0.3...,1	9	**1**

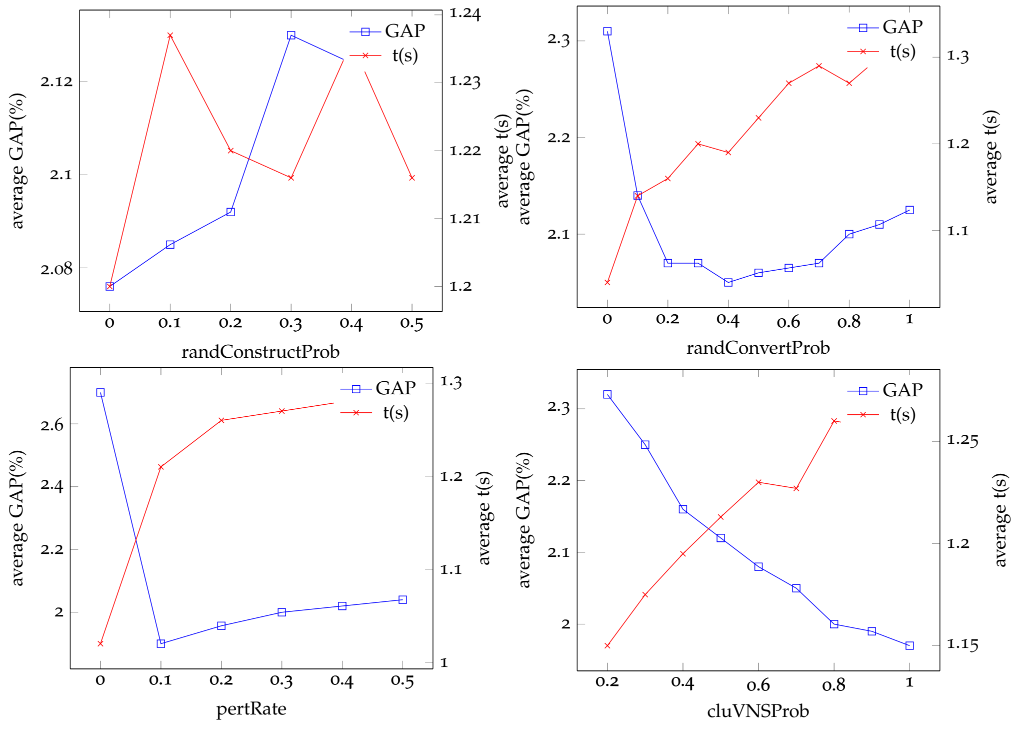


Figure 7.3: Solution quality, measured by the average optimality gap and the average calculation time, for different parameter settings.

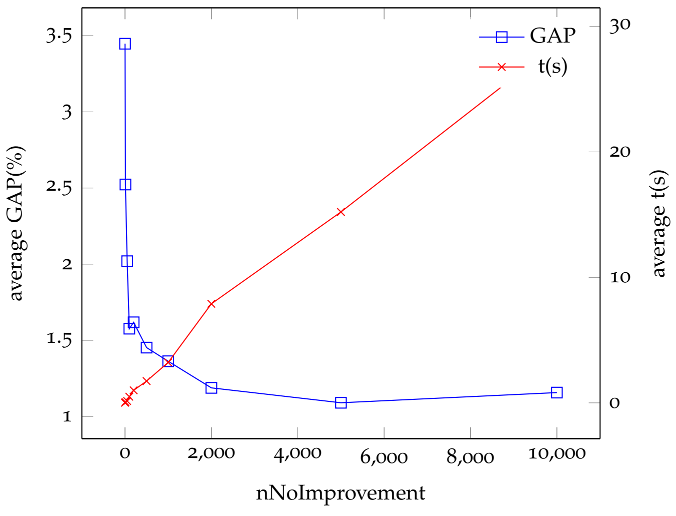


Figure 7.4: Relationship between the number of iterations without improvement (stopping criterion) and the average optimality gap for the tuning instance set.

7.4.2 *Stopping criterion*

The search procedure continues until a stopping criterion is reached. Our algorithm uses a *predefined number of iterations without improvement*. It can be expected that the solution quality will increase for a larger number of allowed iterations. This result is shown in fig. 7.4. This graph is constructed by using the optimal parameter settings, defined above, while varying the maximum number of iterations without improvement. As expected, we find an almost linear relationship between the calculation time and the number of iterations without improvement. A large improvement of the solution quality is realised during the first seconds of execution. As the optimality gap decreases, more calculation time is required to further improve the current solution. To preserve a good balance between computation time and solution quality, the stopping criterion is set to 5000 iterations without improvement.

7.5 **Computational experiments**

The metaheuristic is coded in C++ (MS visual studio) and tested extensively on benchmark instances of different sizes and with varying degree of clustering. All computational results are obtained using an Intel(R) Core(TM) i7-4790 @ 3.60GHz with 16GB of RAM (Linux operating system with wine interface). Because the algorithm uses randomness during the optimisation process, the instances are solved multiple times (20 runs per instance). Both the average and best results are reported per instance. For a complete overview of all obtained solutions, we refer to chapter 10.

7.5.1 *Results on the* GVRPθ3 *instances*

The algorithm is tested on a set of 79 small and medium sized test instances, denoted as GVRPθ3, provided by Battarra, Erdoğan, and Vigo (2014), as discussed in their paper on *exact algorithms for the Clustered Vehicle Routing Problem*. These GVRP instances are adaptations of existing CVRP instances from Bektas, Erdoğan, and Røpke (2011). The transformation is achieved by creating clusters of customers using a seed-based algorithm and by replacing the number of required vehicles by the solution (number of bins) of the bin packing problem for each instance. See Battarra, Erdoğan, and Vigo (2014) for a more elaborate explanation on the design of the instances. The resulting number of clusters reach 88, while the average number of customers per cluster is three.

The obtained results for the GVRPθ3 instances are summarised in table 7.4. By using their branch-and-cut method, Battarra, Erdoğan, and Vigo (2014) are able to solve 77 out of 79 instances exactly within reasonable time limits. It should be mentioned that for these methods the preprocessing times, which lie between 3 and 8 seconds, are not included in the calculation times. This preprocessing step consists of the calculation of all possible Hamiltonian paths inside each cluster. Afterwards, while running the branch-and-cut approach, these results are used to define the optimal inter cluster connections at the customer level for a given sequence of clusters. Our VNS algorithm is able to solve 71 instances to optimality, while significantly reducing calculation times. For the other instances, we are able to provide a high quality solution that lies on average 0.04% from optimality. For the instance G-n262-k25-C88-V9 which could not be solved using the exact approach, a heuristic solution with an objective value of 3310 is obtained in a very short calculation time. For instance M-n200-k16-C67-V6 we improve the upper bound to 909.

Table 7.4: Results for the GVRPθ3 instances. Comparison between the branch-and-cut and price (BCP), branch-and-cut (BC) (Battarra, Erdoğan, and Vigo 2014) and the two-level VNS proposed in this chapter.

		BCP		BC		VNS (20 runs)			
		Opt.	Avg. t(s)	Opt.	Avg. t(s)	Opt.	Avg. t(s)	Avg. best GAP	Avg. GAP
A	31 - 79 cust.	27/27	42.52	27/27	4.84	24/27	0.05	0.07%	0.07%
B	30 - 77 cust.	23/23	7.69	23/23	4.99	21/23	0.04	0.03%	0.04%
P	15 - 100 cust.	24/24	0.48	24/24	3.77	23/24	0.06	0.00%	0.02%
M+G	100 - 261 cust.	2/5	157.25	3/5	25.44	3/5	5.98	0.04%	0.18%
total		76/79		77/79		71/79			
average			26.87		5.86		0.43	**0.03%**	0.04%

7.5.2 *Results on the adapted Golden instances proposed in Expósito-Izquierdo, Rossi, and Sevaux (2016)*

In this section, we test our algorithm on the CLUVRP benchmark instance sets proposed by Expósito-Izquierdo, Rossi, and Sevaux (2016). The instances are adaptations of the instances introduced by Golden et al. (1998) for the CVRP. Each set is characterised by a parameter ρ, representing the filling range of a vehicle. When $\rho = 100\%$, each vehicle can serve at most one cluster, whereas a lower filling percentage indicates that a higher number of clusters can be combined in one vehicle trip. Five different instance sets are built by setting $\rho \in \{10, 25, 50, 75, 100\}\%$.

The two-level solution approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) is compared to the two-level VNS introduced in this chapter. Although both algorithms are based on a breakdown of the CLUVRP in two distinct routing problems, some important differences can be identified. First, Expósito-Izquierdo, Rossi, and Sevaux (2016) define the high-level routing problem by replacing all clusters by their *virtual center* by using the *center of mass concept*. Their approach is therefore limited to Euclidean instances. Secondly, the algorithm by Expósito-Izquierdo, Rossi, and Sevaux (2016) is mainly focused on optimising the solution at the cluster level in which the individual customer sequence is only considered in the Lin-Kernighan heuristic. Our two-level VNS, however, also includes a strong intensification of the low-level routing problem by means of a separate VNS procedure. The results below indicate that it is beneficial to devote additional attention to the solution at the customer level.

The results of both approaches are summarised in tables 7.5 to 7.9. To allow for a fair comparison, a maximum calculation time of 60s is considered for both algorithms.

It can be seen that if $\rho \in \{10, 25, 50\}\%$, almost all instances can be improved by our two-level VNS algorithm compared to the results of Expósito-Izquierdo, Rossi, and Sevaux (2016). The reduction in total cost can be up to 6.10% (instance 4, with $\rho = 10\%$). For the instance sets with a higher filling rate ($\rho \in \{75, 100\}$) it turns out to be harder to improve the current best solution. This might be due to the fact that the lower the number of clusters inside a vehicle, the more the CLUVRP converges to the more traditional CVRP. Therefore we lose the advantage of exploiting the clustered structure of the problem in our algorithm. However, the gaps remain far below 1% compared to Expósito-Izquierdo, Rossi, and Sevaux (2016) for all instances, ensuring that a high quality and competitive solution is found.

Table 7.5: Results for the adapted problem instances by Golden et al. (1998) with $\rho = 10\%$. Comparison between the two-level approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) (column [A]) and the two-level VNS proposed in this chapter.

index	n+1	Q	best known	[A]	two-level VNS	gap
1	240	550	**5759.25**	5801.67	**5759.25**	-0.73%
2	320	700	**9247.92**	9649.67	**9247.92**	-4.16%
3	400	900	**12904.60**	13249.22	**12904.60**	-2.60%
4	480	1000	**17810.40**	18966.92	**17810.40**	-6.10%
5	200	900	**8960.31**	9479.74	**8960.31**	-5.48%
6	280	900	**10976.50**	11601.77	**10976.50**	-5.39%
7	360	900	**12485.80**	13243.13	**12485.80**	-5.72%
8	440	900	**13331.20**	13756.51	**13331.20**	-3.09%
9	255	1000	**710.64**	717.16	**710.64**	-0.91%
10	323	1000	**908.89**	914.73	**908.89**	-0.64%
11	399	1000	**1139.51**	1146.57	**1139.51**	-0.62%
12	483	1000	**1384.29**	1386.48	**1384.29**	-0.16%
13	252	1000	**1030.42**	1047.57	**1030.42**	-1.64%
14	320	1000	**1324.96**	1340.16	**1324.96**	-1.13%
15	396	1000	**1668.39**	1700.28	**1668.39**	-1.88%
16	480	1000	**2053.47**	2097.47	**2053.47**	-2.10%
17	240	200	**840.53**	867.03	**840.53**	-3.06%
18	300	200	**1097.51**	1104.86	**1097.51**	-0.67%
19	360	200	**1522.83**	**1522.83**	1545.53	1.49%
20	420	200	**2019.55**	**2019.55**	2042.90	1.16%
	#best solutions			2	18	

7.5.3 *Results on the adapted Golden instances proposed in Vidal et al. (2015)*

Finally, we test our algorithm on yet another adaptation of the Golden et al. (1998) instance set, proposed by Battarra, Erdoğan, and Vigo (2014). We refer to table 7.10 for an overview of the obtained results. Our two-level VNS is compared to the solution procedure of Expósito-Izquierdo, Rossi, and Sevaux (2016), described above, and the

Table 7.6: Results for the adapted problem instances by Golden et al. (1998) with ρ = 25%. Comparison between the two-level approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) (column [A]) and the two-level VNS proposed in this chapter.

index	n+1	Q	best known	[A]	two-level VNS	gap
1	240	550	**6051.04**	6135.26	**6051.04**	-1.37%
2	320	700	**9725.90**	10005.59	**9725.90**	-2.80%
3	400	900	**13692.60**	14083.28	**13692.60**	-2.77%
4	480	1000	**16977.90**	17359.95	**16977.90**	-2.20%
5	200	900	**9340.70**	9701.89	**9340.70**	-3.72%
6	280	900	**10840.70**	11261.49	**10840.70**	-3.74%
7	360	900	**12348.10**	12720.79	**12348.10**	-2.93%
8	440	900	**14100.80**	14307.64	**14100.80**	-1.45%
9	255	1000	**717.63**	723.49	**717.63**	-0.81%
10	323	1000	**908.26**	915.09	**908.26**	-0.75%
11	399	1000	**1131.84**	1140.36	**1131.84**	-0.75%
12	483	1000	**1387.67**	1395.67	**1387.67**	-0.57%
13	252	1000	**1034.30**	1054.64	**1034.30**	-1.93%
14	320	1000	**1317.05**	1341.39	**1317.05**	-1.81%
15	396	1000	**1667.08**	1697.88	**1667.08**	-1.81%
16	480	1000	**2048.08**	2105.01	**2048.08**	-2.70%
17	240	200	**795.33**	808.24	**795.33**	-1.60%
18	300	200	**1122.73**	1138.45	**1122.73**	-1.38%
19	360	200	**1538.20**	1549.89	**1538.20**	-0.75%
20	420	200	**2036.19**	**2036.19**	2038.27	0.10%
	#best solutions			1	19	

Table 7.7: Results for the adapted problem instances by Golden et al. (1998) with $\rho = 50\%$. Comparison between the two-level approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) (column [A]) and the two-level VNS proposed in this chapter.

index	n+1	Q	best known	[A]	two-level VNS	gap
1	240	550	**6551.04**	6719.17	**6551.04**	-2.50%
2	320	700	**9787.09**	9904.40	**9787.09**	-1.18%
3	400	900	**13287.00**	13303.31	**13287.00**	-0.12%
4	480	1000	**17569.90**	17935.58	**17569.90**	-2.04%
5	200	900	**8597.31**	8790.44	**8597.31**	-2.20%
6	280	900	**10550.80**	10714.34	**10550.80**	-1.53%
7	360	900	**12673.70**	12862.90	**12673.70**	-1.47%
8	440	900	**13766.30**	13924.79	**13766.30**	-1.14%
9	255	1000	**698.04**	703.07	**698.04**	-0.72%
10	323	1000	**890.87**	898.19	**890.87**	-0.81%
11	399	1000	**1107.88**	1112.35	**1107.88**	-0.40%
12	483	1000	**1317.47**	1319.98	**1317.47**	-0.19%
13	252	1000	**1053.47**	1080.84	**1053.47**	-2.53%
14	320	1000	**1342.70**	1363.99	**1342.70**	-1.56%
15	396	1000	**1657.22**	1685.61	**1657.22**	-1.68%
16	480	1000	**2003.10**	2030.60	**2003.10**	-1.35%
17	240	200	**881.66**	910.73	**881.66**	-3.19%
18	300	200	**1200.98**	1217.71	**1200.98**	-1.37%
19	360	200	**1612.33**	1631.21	**1612.33**	-1.16%
20	420	200	**2278.64**	2325.47	**2278.64**	-2.01%
	#best solutions			0	20	

Table 7.8: Results for the adapted problem instances by Golden et al. (1998) with ρ = 75%. Comparison between the two-level approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) (columns [A]) and the two-level VNS proposed in this chapter.

index	n+1	Q	best known	[A]	two-level VNS	gap
1	240	550	**6736.15**	**6736.15**	**6736.15**	0.00%
2	320	700	**10204.30**	**10204.30**	10223.20	0.19%
3	400	900	**13575.70**	**13575.70**	13635.20	0.44%
4	480	1000	**17077.59**	**17077.59**	17194.20	0.68%
5	200	900	**8664.94**	**8664.94**	8666.59	0.02%
6	280	900	**11452.01**	**11452.01**	11520.30	0.60%
7	360	900	**12901.41**	**12901.41**	12950.00	0.38%
8	440	900	**13926.40**	13943.65	**13926.40**	-0.12%
9	255	1000	**773.39**	**773.39**	**773.39**	0.00%
10	323	1000	**1000.51**	**1000.51**	1001.28	0.08%
11	399	1000	**1223.66**	**1223.66**	1226.91	0.27%
12	483	1000	**1475.68**	**1475.68**	1478.86	0.22%
13	252	1000	**1183.12**	**1183.12**	**1183.12**	0.00%
14	320	1000	**1520.55**	1523.44	**1520.55**	-0.19%
15	396	1000	**1825.29**	1829.32	**1825.29**	-0.22%
16	480	1000	**2265.54**	**2265.54**	2265.77	0.01%
17	240	200	**1001.02**	**1001.02**	**1001.02**	0.00%
18	300	200	**1392.15**	1396.27	**1392.15**	-0.29%
19	360	200	**1951.77**	1977.40	**1951.77**	-1.30%
20	420	200	**2540.22**	**2540.22**	2540.39	0.01%
	#best solutions			14	9	

Table 7.9: Results for the adapted problem instances by Golden et al. (1998) with ρ = 100%. Comparison between the two-level approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) (column [A]) and the two-level VNS proposed in this chapter.

index	n+1	Q	best known	[A]	two-level VNS	gap
1	240	550	**6293.04**	**6293.04**	6297.05	0.06%
2	320	700	**9879.59**	**9879.59**	9917.68	0.39%
3	400	900	**12361.09**	**12361.09**	12422.10	0.49%
4	480	1000	**16130.39**	**16130.39**	16276.70	0.91%
5	200	900	**8394.11**	**8394.11**	8399.31	0.06%
6	280	900	**10777.33**	**10777.33**	10802.70	0.24%
7	360	900	**11346.11**	**11346.11**	11411.60	0.58%
8	440	900	**13188.94**	**13188.94**	13251.30	0.47%
9	255	1000	**705.19**	**705.19**	**705.19**	0.00%
10	323	1000	**837.52**	**837.52**	838.55	0.12%
11	399	1000	**1054.13**	**1054.13**	1056.71	0.24%
12	483	1000	**1297.31**	**1297.31**	1300.02	0.21%
13	252	1000	**996.36**	**996.36**	**996.36**	0.00%
14	320	1000	**1223.09**	**1223.09**	1223.41	0.03%
15	396	1000	**1531.29**	**1531.29**	1532.82	0.10%
16	480	1000	**1874.69**	**1874.69**	1875.04	0.02%
17	240	200	**844.27**	**844.27**	**844.27**	0.00%
18	300	200	**1212.97**	**1212.97**	1213.13	0.01%
19	360	200	**1667.45**	**1667.45**	1667.51	0.00%
20	420	200	**2128.60**	**2128.60**	2128.77	0.01%
	#best solutions			20	3	

UHGS$_p$ algorithm from Vidal et al. (2015). The UHGS algorithm aims at combining the diversification strength of a genetic algorithm with the improvement capabilities of local search and has proven to return high quality solutions that are very close to optimality. The algorithm relies, however, on the exact solution of all intra cluster Hamiltonian paths, precomputed by means of Concorde (Applegate et al. 2006). This causes the required calculation time to increase up to even above the exact solution approach of Battarra, Erdoğan, and Vigo (2014). Although in terms of solution quality the UHGS$_p$ method tends to outperform all existing approaches, the high calculation times can be considered an important drawback for some applications.

To allow for the comparison with the results reported by Expósito-Izquierdo, Rossi, and Sevaux (2016), we dedicate a maximum calculation time of 10 seconds to our two-level VNS. On average, this corresponds to a 98% reduction in calculation time compared to Vidal et al. (2015). The two-level VNS is able to find the optimal solution for only 8 out of 220 instances. An optimality gap of around 1% is obtained on average, which is equivalent to a reduction of the optimality gap by 63% compared to Expósito-Izquierdo, Rossi, and Sevaux (2016).

7.6 The clustered vehicle routing problem with weak cluster constraints

7.6.1 *Motivation*

As described above, the CLUVRP with strong cluster constraints requires that all customers that belong to the same cluster should be served consecutively by the same vehicle. This requirement can be relaxed in some real life applications. In parcel delivery, e.g., the customers are often clustered in *zones* (clusters) in order to facilitate the sorting process. These zones are assigned to the available vehicles, obtaining a *tactical plan* in which each vehicle is allowed to serve multiple zones during one trip. (Janssens et al. 2015) However, from the moment that the vehicle leaves the depots there is no need to visit the individual customers according to their original zone. It might be profitable for the driver to leave a current zone, serve customers belonging to another zone and return to the initial zone afterwards. This can depend on the layout of the instance and the individual customer locations, but also on real time traffic information or additional constraints such as time windows. This gives rise to another variant of the CLUVRP, which we define as the *CLUVRP with weak cluster constraints*. Similar to the CLUVRP with strong cluster constraints, we impose that clusters are assigned to vehicles and therefore that all customers that

Table 7.10: Comparison between the UHGS$_p$ algorithm from Vidal et al. (2015) (columns [A]), the two-level approach from Expósito-Izquierdo, Rossi, and Sevaux (2016) (columns [B]) and the two-level VNS proposed in this chapter over the problem instances proposed by Battarra, Erdoğan, and Vigo (2014).

n+1	[A]		[B]		two-level VNS		
	gap	t(s)	gap	t(s)	gap	t(s)	gap reduction
200	0.00%	2866.56	4.61%	10.0	0.07%	10.0	-98.56%
241	0.00%	174.90	2.39%	10.0	0.44%	10.0	-81.66%
252	0.01%	164.69	0.50%	10.0	0.53%	10.0	5.97%
255	0.02%	135.45	3.69%	10.0	1.33%	10.0	-63.93%
280	0.00%	3848.31	2.94%	10.0	0.71%	10.0	-76.00%
300	0.00%	191.26	1.04%	10.0	0.93%	10.0	-11.05%
320	0.02%	198.09	1.26%	10.0	0.85%	10.0	-32.75%
323	0.08%	175.74	4.94%	10.0	0.93%	10.0	-81.22%
360	0.00%	1248.29	2.87%	10.0	1.02%	10.0	-64.52%
396	0.05%	279.15	1.54%	10.0	1.37%	10.0	-10.89%
399	0.06%	198.00	4.96%	10.0	2.15%	10.0	-56.58%
400	0.01%	1384.18	2.56%	10.0	1.26%	10.0	-50.61%
420	0.00%	351.74	2.60%	10.0	1.11%	10.0	-57.22%
440	0.02%	1017.64	3.67%	10.0	1.32%	10.0	-64.02%
480	0.01%	1427.23	3.42%	10.0	1.49%	10.0	-56.38%
483	0.07%	389.16	4.93%	10.0	2.23%	10.0	-54.75%
Average	0.02%	878.15	3.00%	10.0	1.11%	10.0	-62.99%

belong to a certain cluster are all served by the same vehicle. However, we allow a vehicle to leave and re-enter a cluster multiple times during its trip.

7.6.2 *Mathematical model*

The mathematical model, introduced in section 7.2 is adapted below to comply with the weak cluster constraints. Equations (7.7) are relaxed and replace by eqs. (7.16) as each cluster can now be visited multiple times. Furthermore, an additional set of equations is added to the model to ensure that all customers that belong to the same cluster are visited by the same vehicle (see eqs. (7.17)).

$$\min \sum_{(i,j)\in E} \sum_{k\in K} d_{ij} x_{ijk} \tag{7.10}$$

Subject to

$$\sum_{k\in K} y_{ik} = 1 \qquad \forall i \in V \backslash V_0 \tag{7.11}$$

$$\sum_{k\in K} y_{0k} = |K| \tag{7.12}$$

$$\sum_{j\in V\backslash V_0} x_{ijk} = \sum_{j\in V\backslash V_0} x_{jik} = y_{ik} \qquad \forall k \in K, \forall i \in V \tag{7.13}$$

$$\sum_{i\in V} q_i y_{ik} \le Q \qquad \forall k \in K \tag{7.14}$$

$$\sum_{i\in S} \sum_{j\notin S} x_{ijk} \le y_{hk} \qquad \forall Z \subseteq V\backslash V_0, \forall h \in Z, \forall k \in K \tag{7.15}$$

$$\sum_{(i,j)\in\delta^+(C_r)} x_{ijk} = \sum_{(i,j)\in\delta^-(C_r)} x_{ijk} \ge 1 \qquad \forall r \in R \tag{7.16}$$

$$y_{ik} = y_{jk} \qquad \forall i, j \in C_r, \forall k \in K \tag{7.17}$$

$$x_{ijk} \in \{0, 1\} \qquad \forall (i, j) \in E, \forall k \in K \tag{7.18}$$

$$y_i \in \{0, 1\} \qquad \forall i \in V, \forall k \in K \tag{7.19}$$

7.6.3 *Computational experiments*

Our two-level VNS approach is slightly altered to solve the CLUVRP with weak cluster constraints. More specifically, the intra cluster neighbourhoods of the VNS at the customer level are expanded to inter cluster operators, allowing the customers to be moved to any position in the trip.

Again, the GVRPθ3 and Golden instances as proposed by Battarra, Erdoğan, and Vigo (2014) are solved. Table 7.11 bundles the differences in total distance between the CLUVRP with strong and weak cluster constraints. These relative differences are obtained by comparing the results of our algorithm for weak cluster constraints to the results discussed in section 7.5.

As in this section the problem becomes less constrained, the objective value, defined as the total distance travelled by all vehicles, is lower for all instance classes compared to the CLUVRP with hard cluster constraints. The reduction in objective value lies between 4 and 7% on average for the Golden instances, but can go up to more than 12% for some of the instances. As the choice between strong and weak cluster constraints might result in significant differences in total cost, this decision should be taken with care in real life scenarios.

7.7 **Conclusions and future research**

In this chapter, a fast two-level VNS heuristic was presented to solve the Clustered Vehicle Routing Problem. This metaheuristic solution approach solves the CLUVRP without assuming Euclidean distances or converting the problem to a CVRP by using a big-M approach. By integrating a cluster level and a customer level local search phase, the specific clustered structure of the problem was exploited to reduce complexity, and high quality solutions could be obtained in very short calculation times.

Our algorithm was tested on benchmark instances from the literature with different sizes and diverse complexities. Many of the small and medium-sized problems were solved to optimality in very short computing times. Even if the optimal solution was not found, an average optimality gap of 0.03% was obtained. For the large-size instances, which are adaptations of the Golden benchmark instances as proposed by Battarra, Erdoğan, and Vigo (2014) and Expósito-Izquierdo, Rossi, and Sevaux (2016),

Table 7.11: Results for the GVRPθ3 and Golden instances as proposed by Battarra, Erdoğan, and Vigo (2014) with weak cluster constraints. Reported values are the averaged over all instances in the set, compared to the obtained results with strong cluster constraints.

gvrpθ3				Golden instances			
instance set	**t(s)**	**Avg. best difference**	**Avg. difference**	**n+1**	**t(s)**	**Avg. best difference**	**Avg. difference**
A	0.28	-2.66 %	-2.52 %	200	10.00	-8.97 %	-8.09 %
B	0.06	-1.18 %	-1.18 %	241	10.00	-5.69 %	-4.92 %
P	0.52	-4.64 %	-4.58 %	252	10.00	-3.62 %	-3.04 %
M+G	13.46	-3.19 %	-2.73 %	255	10.00	-5.02 %	-3.88 %
				280	10.00	-6.57 %	-5.56 %
				300	10.00	-3.81 %	-3.09 %
				320	10.00	-3.46 %	-2.88 %
				323	10.00	-6.10 %	-4.98 %
				360	10.00	-5.23 %	-4.48 %
				396	10.00	-3.13 %	-2.41 %
				399	10.00	-4.67 %	-3.48 %
				400	10.00	-3.81 %	-3.20 %
				420	10.00	-3.49 %	-2.71 %
				440	10.00	-4.25 %	-3.37 %
				480	10.00	-3.87 %	-3.15 %
				483	10.00	-2.96 %	-1.63 %
average	1.12	-2.86 %	-2.80 %			-4.65 %	-3.82 %

only a limited number of optimal solutions were found. However, with an average optimality gap around 1% high quality and competitive solutions were obtained by our two-level VNS approach in very small computation times. We therefore believe that our solution approach has potential for integration in solution approaches that rely on the CLUVRP as a subproblem as this might require the method to be executed multiple times. For example, a courier company that wants to determine the boundaries of its zones (cluster) in the distribution area might want to solve the CLUVRP for every possible configuration to select the best option. In this context, a fast method is preferred while the remaining optimality gap is a minor issue. By allowing larger calculation times, the optimality gap is likely to reduce further. However, we leave this trade-off to the decision maker.

Furthermore, we have introduced a new type of CLUVRP in this chapter. Next to the traditional CLUVRP with strong cluster constraints, in which it is not allowed to leave a cluster before having served all customers within it, we have proposed a CLUVRP variant with weak cluster constraints. Here, all customers belonging to the same cluster should be served by the same vehicle but customers in the different clusters assigned to a vehicle can be visited in any order. Our simulation experiments show that the total distance travelled might decrease by 4.65% on average for the large-size instances when going from strong to weak cluster constraints. For some instances, a cost reduction of more than 10% could be obtained. These values put an estimate on the profit of allowing the approach with weak cluster constraints as opposed to strong cluster constraints, e.g., in the context of the operations of a courier company.

Although all algorithms are tested and compared on multiple sets of benchmark instances, a gap remains between the size of these instances and the complexity of the logistics problems faced by the industry today. For further research, we therefore acknowledge the need for additional very large-size instances that are able to better represent the daily planning problems faced by, e.g., parcel delivery and courier companies.

Acknowledgements

For the current chapter, the authors would like to thank Maria Battarra (University of Southampton) for sharing the test instances and optimal results.

8

Integrated framework

Abstract:

In this chapter a general solution framework is presented for optimising decisions in a horizontal logistics cooperation. The framework distinguishes between the objective of the group and the objectives of the individual partners in the coalition. Although the importance of the individual partner interests is often acknowledged in the literature, the proposed solution framework is the first to include these objectives directly into the objective function of the optimisation model. The solution framework is applied to a collaborative variant of the clustered vehicle routing problem, for which we also create a set of benchmark instances.

We find that by only considering a global coalition objective the obtained solution is often suboptimal for some partners in the coalition. Providing a set of high quality alternative solutions that are Pareto-efficient with respect to the partner objectives, gives additional insight in the sensitivity of a solution, which can support the decision making process. Our computational results therefore acknowledge the importance of including the individual partner objectives into the optimisation procedure.

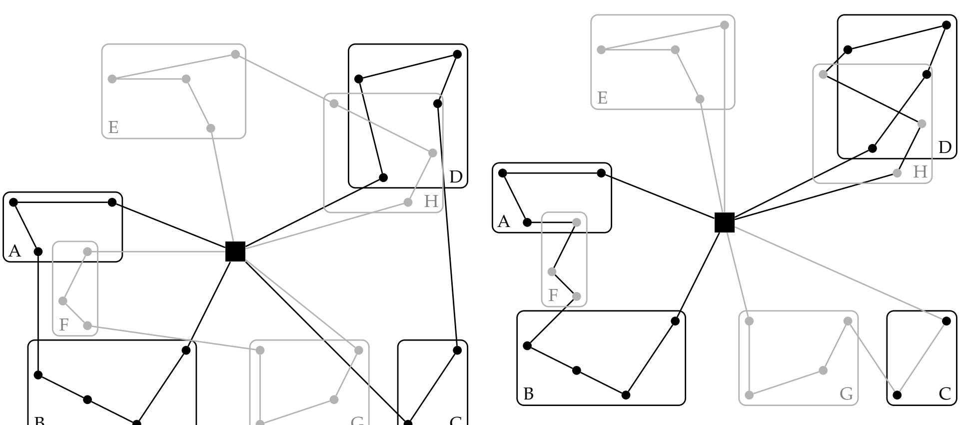
8.1 Problem statement: The clustered vehicle routing problem

The Clustered Vehicle Routing Problem (CLUVRP) is a generalization of the classical Capacitated Vehicle Routing Problem (CVRP) in which customers are grouped into predefined clusters. The problem is more constrained compared to the CVRP, as in the CLUVRP all customers that belong to the same cluster should be served consecutively by the same vehicle.

Introduced by Sevaux and Sörensen (2008), the CLUVRP can be used to model the parcel delivery activities of courier companies, such as FedEx or UPS. For such large courier companies, shipping millions of packages a day, it is not unusual to execute several thousand stops from a depot using hundreds of vehicles. The use of zones (or clusters) is acknowledged by many authors as a way to reduce the problem size and to avoid the need for detailed customer information during the planning phase. (Janssens et al. 2015; Lin, Yan, and Lai 2013; Mourgaya and Vanderbeck 2007; Zolezzi and Rudnick 2002)

For the mathematical model formulation of the CLUVRP, we refer to chapter 7. In what follows, the solution space bounded by the eqs. (7.2) to eqs. (7.9) is denoted as ζ. A solution vector x is said to be a feasible solution for the above-mentioned CLUVRP if $x \in \zeta$.

8.1.1 *The collaborative environment*



(a) Stand-alone scenario

(b) Cooperative scenario with cluster exchange

Figure 8.1: The collaborative result for the clustered vehicle routing problem.

We consider a grand coalition N, representing a horizontal cooperation between n courier companies $p \in N$. Let S be any subcoalition of N, such that $S \subseteq N$. In contrast to the stand-alone scenario in which all companies are only responsible for serving their own customer clusters, we allow for the transfer of clusters from one partner to another partner in the coalition. In this way, we encourage that each cluster is served by the partner that can fulfil the corresponding transportation requests in the most efficient way. This is visualised in fig. 8.1. Here, a two-partner coalition is represented. Both companies operate from the central depot depicted by the square. The first partner, represented in black, needs to deliver goods to customers located in four clusters (A, B, C and D) using two vehicles. The two resulting vehicle trips, obtained by solving the CLUVRP for this partner, are visualised by the black edges. A similar approach can be used to calculate the optimal operational plan for the second (gray) partner in which clusters E, F, G and H are served. Even though both companies have fully optimised their own logistics operations internally, it is likely that a more efficient operational plan can be constructed when considering horizontal cooperation. A collaborative logistics model is to be solved, taking all transportation requests of both partners into account. The following objectives are identified.

8.1.2 *Coalition objective*

In the non-collaborative definition of the CLUVRP, presented in section 7.2, the minimisation of the total distance driven by all vehicles is the main (and only) objective. By extrapolating this to the coalition, we assume that all partners agree on the common objective to reduce the total distance-based cost of the whole coalition as much as possible. This objective is referred to as the coalition objective $F_c(x)$ and is calculated as the sum of the distance-based cost of the CLUVRP solution obtained for every partner.

$$F_c(x) = \sum_{p \in N} \Big(\sum_{(i,j) \in E} \sum_{k \in K} d_{ij} x_{ijk} \Big)_p$$

8.1.3 *Partner objectives*

With or without horizontal cooperation, the aim of each individual company will remain to deliver its customers in the most cost effective way. We therefore argue that a company is likely to prefer the solution that costs him the least. The fraction of the total coalition cost that should be paid by an individual partner is determined by the applied *cost allocation mechanism* and denoted as ψ_p. Given a predefined cost allocation method, for each partner, the partner objective is defined as the minimisation of the cost to be paid by that partner. As a result, we obtain a multi-objective optimisation model with dimensionality equal to the number of partners (n).

$$\forall p \in N : F_p(x) = \psi_p$$

8.2 **Integrated solution approach**

In the current section, the integrated solution approach for tackling collaborative logistics optimisation problems is presented. We first introduce a general framework, after which it is further specified for the CLUVRP.

8.2.1 *General framework*

We consider a horizontal logistics cooperation of n partners optimising their operational planning. The main motivation for the group to invest in this long-term relationship is given by a common goal on which all partners agree, i.e., the *coalition objective*. The following model shows the (generalised) optimisation model at the coalition level,

$$F_c(x^*) = \min\left(F_c(x)\right)$$

Subject to

$$x \in \zeta$$

in which $F_c(x)$ is defined as the *coalition objective* and a solution vector $x \in \zeta$ is to be determined such that the coalition objective is minimised. We will refer to this problem as the *Coalition Level Optimisation Problem (CLOP)*. The definition of the solution space ζ will depend on the logistics problem studied. Let x^* be the best-known solution vector and $F_c(x^*)$ the corresponding value of the objective function. In the cooperative logistics context described before, x^* can be interpreted as the best possible solution for the coalition as a whole considering only the coalition objective.

Now, each collaborating company is given the opportunity to express which characteristics of the solution x it deems important. This gives rise to another set of objective functions, i.e., the *partner objectives*. These objectives, denoted as $F_i(x)$, with $i = \{1, \ldots, k\}$, should assure that all partners evaluate the proposed solutions as beneficial and therefore do not have the intention to leave the coalition. Each partner is free to impose either none, a single, or multiple additional objectives to the optimisation procedure.

Let $d(a, b)$ be a distance measure between two solutions $a, b \in \zeta$, and let ϵ, be a parameter that states the acceptable deviation from the optimal coalition solution. Now, define the acceptable region of x^* as follows:

$$\mathcal{R}(x^*) = \{x | d(x, x^*) \leq \epsilon\} \tag{8.1}$$

The neighbourhood of x^* comprises all solution vectors $x \in \zeta$ that are within a distance ϵ from x^* with respect to the coalition objective value. In this chapter we will consider the distance between solutions $a, b \in \zeta$ to be equal to their difference in coalition objective value.

$$d(a, b) = |F_c(a) - F_c(b)| \tag{8.2}$$

We now define the *Partner Level Optimisation Problem (PLOP)* as a multi-objective optimisation problem that includes all partner objectives as follows:

$$\min_{x \in \zeta} (F_1(x), \ldots, F_k(x))$$

Subject to

$$x \in \mathcal{R}(x^*)$$

The result of this multi-objective optimisation model is a Pareto set of non-dominated solutions with respect to the individual partner objectives. Furthermore, we assure that all reported solutions remain close to the optimal solution at the coalition level. In this way, the size of the solution space is reduced by focusing only on the most promising solutions that ensure a certain level of efficiency for the coalition as a whole. This approach also allows controlling the size of the solution set provided to the decision maker by varying the size of the acceptable region.

As a conclusion, the general solution framework requires two optimisation problems to be solved. First, in the Coalition Level Optimisation Problem (CLOP), the routing problem is defined and solved at the level of the coalition, considering only the coalition objective. Second, the multi-objective Partner Level Optimisation Problem (PLOP), containing all individual partner objectives, is to be solved. In the following sections, both problems are studied in more detail by applying them to the collaborative CLUVRP example.

8.2.2 CLUVRP *coalition level optimisation problem (CLOP)*

As stated in section 8.1.2, the coalition as a whole considers the minimisation of the total logistics cost as its only objective. This total coalition cost is calculated as the sum of the routing costs incurred by each individual partner in the final solution. The aim of the CLOP is therefore to determine a set of routes for each partner, in such a way that the total cost of all these routes is minimised. As we require that all vehicles are used, the number of routes allocated to each partner should equal the number of vehicles each partner has available. K^p is the set of vehicles for partner p, so the set of available vehicles at coalition level $K^c = \bigcup_{p \in N} K^p$, under the assumption that $\bigcap_{p \in N} K^p = \emptyset$. Similarly, the aggregated set of all customers that should be visited by all partners in the coalition is represented by $V^c = \bigcup_{p \in N} V^p$ in which V^p is the set of vertices that belong to partner p. Without loss of generality, it is assumed that all partners operate from the same depot (V_0) and no customers are shared. This means that each customer is linked to only one of the partners.

The goal of the CLOP is to construct $|K^c|$ vehicle routes, in such a way that all transportation requests of all partners in the coalition are executed and the total logistics cost is minimised. From the perspective of the coalition as a whole, this aggregated problem equals the classic CLUVRP, and can therefore be solved by any (non-collaborative) solution technique available in the literature. In this chapter, we will make use of the two-level solution approach proposed in Defryn and Sörensen (2017a) as the algorithm has been proven to provide good solutions in very short calculation times.

The result of this phase is a single solution for the CLUVRP defined at the coalition level. This solution is considered the *best possible outcome for the coalition as a whole* as it is optimised with respect to the coalition objective.

8.2.3 CLUVRP *partner level optimisation problem (PLOP)*

The PLOP can be considered a multi-objective variant of the aggregated logistics optimisation problem defined in section 8.2.2. The goal is to fulfil all transportation requests from all partners in the coalition in such a way that all individual partner objectives are optimised. Due to the multi-objective character of the problem, the optimal solution set is no longer a singleton, but a Pareto set of non-dominated solutions.

The solution space for the CLUVRP variant studied in this chapter is visualised in fig. 8.2. For illustrative purposes we limit ourselves to a two-partner coalition, however our conclusions can easily be extended to instances with more than two partners. The costs allocated to partner 1 and 2 are denoted on the horizontal and vertical axis respectively. The result of the stand-alone scenario is denoted by the point SA, and point CE is the optimal result obtained by solving the CLOP. The Pareto front is represented by the solid line. Because we defined the coalition objective as the minimisation of the total cost, CE is an element of the Pareto set. This is explained by the fact that the total cost equals the sum of all costs allocated to the individual partner (in our case $F_c(\text{CE}) = \psi_1 + \psi_2$). Therefore, no solution exists that has a lower value for both ψ_1 and ψ_2.

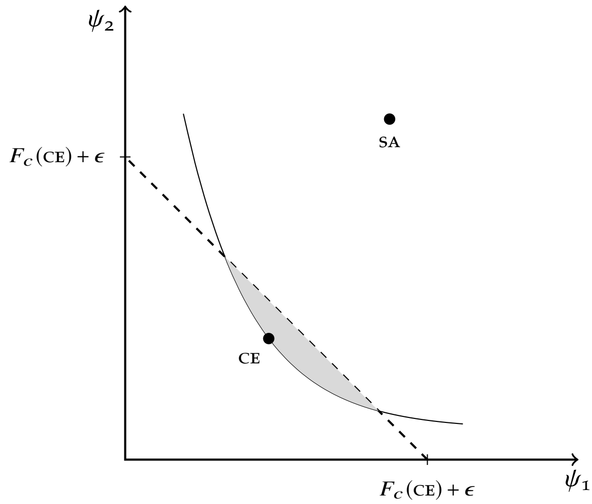


Figure 8.2: Visual representation of the acceptable region $\mathcal{R}(\text{CE})$ of the coalition-efficient solution in a two-partner coalition for our CLUVRP example.

8.2.3.1 *Optimisation through cluster exchange*

To ensure that all customers belonging to the same cluster remain grouped in the same vehicle, we state that only complete clusters can be exchanged between partners. Therefore, each solution for the collaborative variant of the CLUVRP differs in the way the clusters are allocated to the individual partners. An allocation of clusters to the partners is referred to as a *cluster configuration*. If Ω is the set of all possible cluster configurations, then the aim of the PLOP is to find these routing solutions resulting from cluster configurations $\omega \in \Omega$ for which the individual partner objectives are Pareto-efficient.

To reduce the search on irrelevant parts of the solution space, and to provide the decision makers with a set of solutions that score well on both the coalition objective and the individual partner objectives, we focus only on the solutions that stay within a predefined distance ϵ from the coalition-efficient solution CE and therefore belong to its acceptable region $\mathcal{R}(\text{CE})$, as defined in eq. (8.1) and visualised by the grey zone in fig. 8.2. $\mathcal{R}(\text{CE})$ contains all solutions for the coalition with a total logistics cost smaller than $F_c(x) + \epsilon$. Instead of constructing the whole Pareto frontier, the problem is now reduced to finding the set of non-dominated solutions that belong to $\mathcal{R}(\text{CE})$. This means that for the CLUVRP the problem is reduced to approximating only the part of the Pareto frontier that forms the border of $\mathcal{R}(\text{CE})$. As we expect very similar configurations to result into a comparable total coalition cost, we propose a local search based approach to explore alternative cluster configurations.

8.2.3.2 *Search strategy*

To approximate the part of the Pareto frontier that belongs to $\mathcal{R}$(CE), we make use of an iterative procedure. At each iteration, all cluster configurations in the current Pareto optimal solutions are explored with respect to the neighbourhoods defined in table 8.1.

Table 8.1: Definition of the local search neighbourhoods used for exchanging the clusters.

Neighbourhood	**Definition**
SWAP2	Swap the partner of two clusters.
RELOCATE	Change the partner of one of the clusters.

By changing the subset of clusters to be visited by each partner, the routing solution should be re-optimised by solving a CLUVRP for every (affected) partner. As this is done for every cluster configuration that can be reached from all solutions currently in the Pareto frontier with a given move type, a set of alternative but very similar routing solutions is generated (the difference in cluster configurations is only one move and the operators are not very disruptive). Because of this similarity, we also expect the total cost of these new solutions to be relatively close to the total cost of the initial Pareto-efficient solution, so it is likely that these new solutions belong to $\mathcal{R}$(CE). The pseudocode of the proposed optimisation algorithm is presented in algorithm 3.

8.3 **Computational experiments**

8.3.1 *Benchmark instances*

In the literature, no benchmark instances are available for a multi-partner CLUVRP as this problem has never been studied before. We therefore adapt the GVRPθ3 (set A) instances provided by Battarra, Erdoğan, and Vigo (2014) to comply with the multi-partner environment by including the following additional specifications. Coalitions with up to four partners are considered ($n \in \{2, 3, 4\}$). It is ensured that

Algorithm 3 Pseudocode for the local search based algorithm to tackle the PLOP.

```
NBH = set of available neighbourhoods;
k = 1;
paretoSet = {CE};
alternativeSet = ∅;
do
    for all x ∈ paretoSet do
        alternativeSet ← generateClusterConfigurations(k);
        for all x′ ∈ alternativeSet do
            re-optimiseRouting(x′);
            if x′ ∈ R(x) then
                allocateCosts(x′);
                checkDominance(x′, paretoSet);
                updateParetoSet(x′, paretoSet);
            end if
        end for
    end for
    if paretoSet has changed then
        k ← 1;
    else
        k ← k + 1;
    end if
while k ≤ |NBH|;
```

the grand coalition size is at most equal to the total number of available vehicles ($|K^c|$) so each partner has at least one vehicle. Furthermore, each cluster is allocated to only one partner. This is done in a random way to avoid that all clusters that belong to the same partner are geographically grouped in the same part of the distribution area. However, the feasibility of the stand-alone scenario is guaranteed by making sure that for each partner enough vehicles are available to serve at least its own clusters. The instances are available upon request.

8.3.2 *Cost allocation method*

To divide the cost of a shared vehicle trip among all partners involved, a volume-based allocation rule is applied. This method divides the total coalition cost proportional to the demand of each partner in the current vehicle trip. For each vehicle trip $k \in K^c$, the total cost allocated to partner p is calculated according to eq. (8.3).

$$\psi_p = \frac{\sum_{i \in V^p} q_i y_{ik}}{\sum_{i \in V^c} q_i y_{ik}} \sum_{(i,j) \in E} d_{ij} x_{ijk} \tag{8.3}$$

The volume-based allocation rule is selected because it is straightforward and often used in real-life cases. In this way we could also reduce the complexity of the allocation mechanism and focus more on the multi-objective logistics optimisation itself. Choosing another cost allocation mechanism is likely to significantly alter the numerical allocation results (Defryn, Vanovermeire, and Sörensen 2015). However, we do not expect this to affect the general conclusions drawn in this chapter.

8.3.3 *Simulation results*

The integrated solution framework is coded in C++ (MS visual studio) and tested on the generated benchmark instances for different values of ϵ, expressed as a percentage α of $F_c(\text{CE})$ with $\alpha \in \{0.01, 0.05, 0.10\}$. All computational results are obtained using an Intel(R) Core(TM) i7-4790 @ 3.60GHz with 16GB of RAM (Linux operating system with wine interface). All results for $\alpha = 0.05$ are presented in tables 8.2 to 8.3. For a detailed overview of all other scenarios we refer the reader to chapter 11.

Table 8.2: Detailed results for the two-partner COLGVRPθ3 instances with α = 0.05.

instance					grand coalition			partner 1			partner 2			Pareto set	
					total cost		max.	profit			profit				
n	k	C	V	p	sa	ce	profit	ce	min	max	ce	min	max	size	
32	5	11	2	2	634	522	18%	**15%**	15%	15%	**22%**	22%	22%	1	
33	5	11	2	2	578	472	18%	**19%**	15%	19%	17%	14%	20%	3	
33	6	11	2	2	676	562	17%	24%	16%	27%	6%	-10%	16%	4	✗
34	5	12	2	2	651	547	16%	**25%**	23%	25%	5%	5%	7%	2	
36	5	12	2	2	746	589	21%	**26%**	26%	26%	**15%**	15%	15%	1	
37	5	13	2	2	677	569	16%	17%	17%	18%	**15%**	8%	15%	2	
37	6	13	2	2	733	615	16%	21%	21%	23%	**10%**	6%	10%	3	
38	5	13	2	2	692	507	27%	**37%**	37%	37%	**13%**	13%	13%	1	
39	5	13	2	2	751	618	18%	33%	33%	35%	**-1%**	-2%	-1%	3	
39	6	13	2	2	765	613	20%	**33%**	33%	33%	**0%**	-5%	0%	2	
44	6	15	2	2	811	729	10%	-1%	-2%	3%	19%	18%	23%	3	✗
45	6	15	3	2	776	712	8%	14%	2%	16%	-2%	-9%	8%	8	✗
45	7	15	3	2	818	664	19%	**13%**	13%	13%	**29%**	29%	29%	1	
46	7	16	3	2	801	664	17%	18%	16%	24%	15%	1%	17%	11	✗
48	7	16	3	2	836	683	18%	15%	15%	19%	**23%**	16%	23%	4	
53	7	18	3	2	817	651	20%	17%	16%	21%	**24%**	16%	24%	5	
54	7	18	3	2	873	724	17%	15%	6%	16%	20%	13%	30%	8	✗
55	9	19	3	2	795	653	18%	**14%**	11%	14%	**25%**	25%	25%	2	
60	9	20	3	2	904	795	12%	**8%**	4%	8%	19%	21%	22%	2	
61	9	21	4	2	832	682	18%	**26%**	15%	26%	11%	11%	14%	6	
62	8	21	3	2	910	778	15%	**12%**	12%	12%	**20%**	9%	20%	4	
63	9	21	3	2	1029	865	16%	10%	2%	9%	26%	25%	29%	4	✗
63	10	21	4	2	994	801	19%	**29%**	29%	29%	**10%**	10%	10%	1	
64	9	22	3	2	906	776	14%	**18%**	10%	18%	8%	8%	14%	7	
65	9	22	3	2	839	749	11%	6%	8%	8%	18%	22%	22%	1	✗
69	9	23	3	2	931	839	10%	1%	-7%	10%	23%	8%	32%	17	✗
80	10	27	4	2	1197	974	19%	36%	26%	38%	-1%	-8%	6%	17	✗

Table 8.3: Detailed results for the COLGVRPθ3 instances with more than two partners with $\alpha = 0.05$.

instance					grand coalition			partner 1			partner 2			partner 3			partner 4			Pareto set	
					total cost		max.		profit			profit			profit			profit			
n	k	C	V	p	sa	ce	profit	ce	min	max	ce	min	max	ce	min	max	ce	min	max	size	
45	6	15	3	3	999	712	29%	58%	51%	59%	-2%	-17%	8%	14%	0%	20%				11	✗
45	7	15	3	3	938	664	29%	31%	26%	37%	**29%**	17%	29%	**27%**	13%	27%				8	
46	7	16	3	3	947	664	30%	55%	42%	57%	15%	-1%	17%	14%	8%	25%				33	✗
48	7	16	3	3	960	683	29%	41%	32%	43%	**23%**	8%	23%	22%	17%	30%				24	✗
53	7	18	3	3	986	651	34%	46%	39%	49%	24%	16%	26%	32%	25%	37%				28	✗
54	7	18	3	3	997	724	27%	**22%**	10%	22%	20%	13%	26%	43%	40%	51%				13	
55	9	19	3	3	998	653	35%	**44%**	42%	44%	25%	25%	26%	**33%**	25%	33%				5	
60	9	20	3	3	1051	795	24%	**29%**	26%	29%	19%	18%	22%	24%	22%	25%				10	
62	8	21	3	3	1050	778	26%	**38%**	33%	38%	**20%**	9%	20%	15%	11%	20%				18	
63	9	21	3	3	1076	895	17%	12%	4%	14%	25%	15%	26%	12%	10%	15%				9	✗
64	9	22	3	3	1101	779	29%	39%	29%	42%	8%	0%	14%	36%	22%	42%				42	✗
65	9	22	3	3	996	796	20%	35%	20%	40%	8%	-3%	26%	13%	5%	22%				32	✗
69	9	23	3	3	1052	829	21%	26%	12%	29%	23%	18%	33%	13%	-4%	19%				38	✗
61	9	21	4	4	1134	682	40%	53%	50%	58%	46%	38%	47%	**43%**	33%	43%	13%	8%	20%	23	
63	10	21	4	4	1217	801	34%	**54%**	48%	54%	30%	21%	32%	13%	10%	15%	32%	23%	34%	4	

For the grand coalition, the summed stand-alone cost of all partners is given in column SA and the total cost of the best solution at the coalition level is listed in column CE. Our results confirm that setting up a horizontal logistics cooperation is beneficial as double-digit profits are obtained for almost all instances. For the two-partner instances, the average coalition profit is around 16.5%. For the three- and four-partner instances these potential profits increase to around 26% and 34.5% respectively. This increase is explained by the fact that larger coalitions can create more opportunities for optimisation. For every partner p the relative profit is calculated by comparing its stand-alone cost $c(\textsc{sa}_p)$ with the allocated cost ψ_p according to eq. (8.4).

$$\text{profit}(\%) = \frac{c(p) - \psi_p}{c(p)} \tag{8.4}$$

The profit realised by each partner when choosing the coalition-efficient solution is denoted in its column CE. The columns MIN and MAX give the range in which the relative profit of the partner varies over all Pareto-efficient solutions. It can be seen that for instances with a Pareto-size of 1, the coalition-efficient solution CE is the most profitable option for all partners, as there is no alternative solution available. In all other scenarios, at least one partner is able to improve its situation by selecting another solution from the Pareto set. For instances *n39-k6-C13-V2-p2* and *n62-k8-C21-V3-p2* in table 8.2, the differences in the values of the partner objectives over all Pareto-efficient solutions are smaller than 1% for each individual partner. In such situation, the partners will likely be indifferent with respect to all Pareto-efficient solutions. These additional insights in the sensitivity of a solution, gained by providing a set of high quality alternative solutions instead of only CE, can support the decision making process.

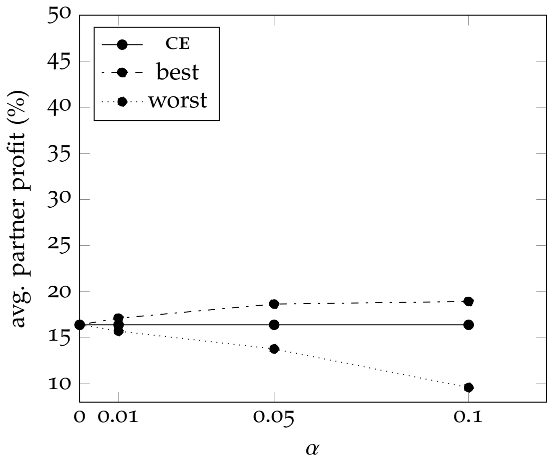
For all instances marked with a ✗, the coalition-efficient solution is even suboptimal for all partners in the coalition. This means that from the list of alternative solutions, each partner will prefer a solution that is different from CE (i.e., the solution scores better on the individual partner objective). However, the preferred solution differs among the partners. The higher the value of α, the larger the neighbourhood $\mathcal{R}(\textsc{ce})$ and the higher the probability that all partners can improve their individual situation by diverging from the coalition-efficient solution. Furthermore, we notice that although all solutions guarantee that the global efficiency of the coalition is high (only solutions in the neighbourhood $\mathcal{R}(\textsc{ce})$ are considered), individual differences for the partners can be significant. For example in instance *n33-k6-C11-V2-p2*, the relative profit margin for partner 2 ranges from -10% up to 16%. These results acknowledge the importance of including individual partner preferences into the optimisation procedure.

The effect of parameter α on the constructed Pareto frontier is visualised in fig. 8.3. In this figure, the average profit obtained by choosing the coalition efficient solution is compared by respectively the best and the worst average profit for an individual partner over all instances. When α equals zero, the acceptable region $\mathcal{R}(\textsc{ce})$ contains only CE. For increasing values of α, the results for each individual partner start to diverge significantly. We also observe that the difference in individual profit tends to be more sensitive in the negative direction. This was expected as all solutions have a total coalition cost that is higher than the cost of solution CE. Our results show that a small change in the solution, with relatively limited impact on the coalition objective, might have a significant impact on the objective function of the partners in the coalition. A change in total coalition cost of maximum 5% ($\alpha = 0.05$) results in a solution set in which the cost allocated to an individual partner differs by 5.87% on average. For a three- and four-partner coalition, these individual differences increase to 12.46% and 9.25% respectively.

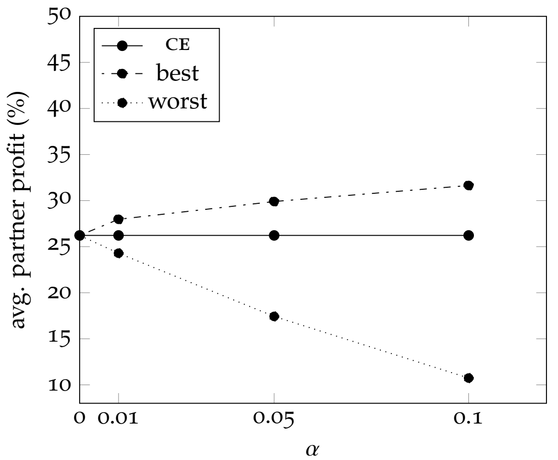
For some instances we found negative profits for one of the partners. This is due to the fact that the volume-based allocation method does not guarantee the property of *individual rationality* (see also section 3.5).

8.4 Conclusions and future research

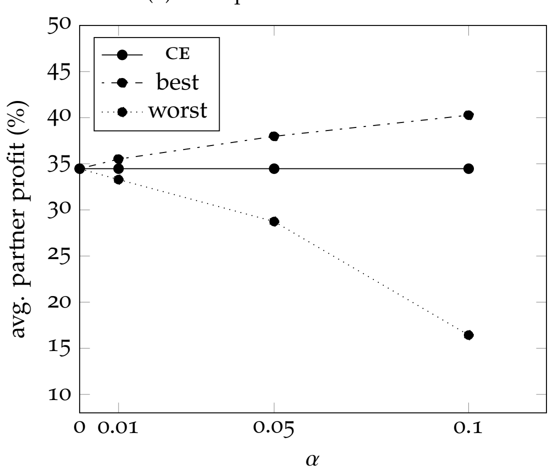
Existing research on horizontal logistics cooperation has mainly focused on assessing costs and benefits, and their allocation to individual collaborating partners. This chapter is the first to propose a modelling framework and solution method to explicitly take both the coalition and individual partner objectives into account. To focus ideas, a horizontal logistics cooperation is considered in which up to four companies jointly optimise their logistics operations. The collaboration is modelled as a clustered vehicle routing problem, in which customers belonging to a predefined cluster are served consecutively by the same vehicle. Besides a global objective at the coalition level, we allowed each individual partner to express additional (personal) objectives. We presented a general integrated solution framework that takes both the objective of the coalition and the individual partner interests into account. The



(a) two-partner instances



(b) three-partner instances



(c) four-partner instances

Figure 8.3: Average partner profit for all solutions in the Pareto set.

framework combines both levels of objective by sequentially solving two optimisation problems: the Coalition Level Optimisation Problem (CLOP) and the Partner level Optimisation Problem (PLOP). Through the definition of the neighbourhood $\mathcal{R}(\text{ce})$ it is guaranteed that only solutions are returned by the PLOP that score also high in the CLOP.

Based on computational experiments on benchmark instances from the literature, we observe that even if horizontal cooperation is beneficial for the coalition, we showed that a slightly inferior solution for the group as a whole might result into (much) better solutions for one or more partners in the coalition. These results show the importance of selecting an appropriate cost allocation mechanism and the value of α. Also, opposed to existing literature on logistics cooperation we therefore recommend giving decision makers a set of alternative solutions. The insight into the sensitivity of both the coalition objectives and the individual partner objectives can result in a higher long-term stability and success of the collaboration.

However, including partner objectives increases the complexity of the logistics optimisation problem. We believe that this offers interesting avenues for further research.

Part IV

DISCUSSION

9

General conclusions

The introduction of low emission zones near large cities, kilometre-based toll charges for trucks on the European highways, growing success of e-commerce, increasing pressure for fast (just in time) deliveries of small batches, increasing fuel prices, ongoing debates on environmental issues, globalisation, ... These are only a few examples of today's challenges in supply chain management and they force companies to rethink their operations in order to remain competitive. As shown in chapter 1, our current logistics system, and more specifically road transportation of goods, lacks efficiency and shows room for improvement. horizontal logistics cooperation (HLC) is considered a viable way to increase the efficiency of transportation activities, as it can result in a lower total cost while even increasing the customer service level (number of drops, ...). Through active synchronisation of transportation flows, additional bundling opportunities might appear and companies are able to exploit economies of scale.

9.1 Contributions to the research community

Horizontal cooperation in logistics has received increased attention from the research community, especially over the last ten years. The existing contributions, however, are still scarce and scattered, and no solid frameworks or approaches for analysing and solving logistics optimisation problems in the context of horizontal cooperation exist. The research is mainly focused on (i) proving the potential of HLC by means of simulation experiments or the reporting on actual case studies, and (ii) the definition and selection of an appropriate allocation rules for dividing the total coalition cost (or profit) among the collaborating partners.

This dissertation is the first attempt towards the definition of a general framework for tackling logistics planning problems that involve multiple partners. Whereas existing contributions generally consider traditional (non-collaborative) logistics optimisation techniques to tackle collaborative problems, the first *multi-partner optimisation techniques* are developed in this thesis. More specifically, we focused on two main aspects: (i) the inclusion of allocation rules (part ii of this thesis) and (ii) a multi-objective approach with multiple levels of decision making (part iii). To the best of our knowledge, such a view on collaborative logistics problems has never been considered before.

The interaction between the operational and tactical level of decision making is studied empirically (chapter 4) and theoretically (chapter 5). The main takeaway of these chapters was that the inclusion of appropriate allocation rules to divide workload, costs, benefits or resources among the collaborating partners is required in a multi-partner context. These allocation rules can be included in the optimisation procedure or added as a post-processing step. Although often the case in current research, not taking such allocation rules into account at all should be discouraged.

The search for an appropriate allocation method is currently often solely based on *fairness* criteria. We showed, however, that these allocation rules are able to provide incentives to the individual partners. As these incentives might differ significantly for different methods, we argue that they should also be considered when deciding on an allocation rule. In other words, a good method should ensure that if a partner is willing to do something that is considered beneficial by the coalition, this action is rewarded by the allocation rule.

In part iii, we developed three solution models for tackling collaborative logistics problems with multiple levels of objectives: the coalition efficiency model, the partner efficiency model and an integrated model. These models differ in the level at which the optimisation procedure takes place. The coalition efficiency model was defined as a four-step procedure in which the logistics problem is first solved by taking only the coalition objective(s) into account. From the moment that a solution set is obtained for the coalition, the individual partner objectives are used solely to differentiate among these solutions and select only the subset of solutions that are not dominated according to the individual partner objectives (if such solutions exist). This is in contrast to the partner efficiency model, which gives full priority to the individual partner objectives. The resulting solution set returned by the partner efficiency model therefore guarantees Pareto efficiency with respect to all partner objectives without assuring that the coalition as a whole is performing efficiently. Finally, the integrated model combines the coalition efficiency model and the partner efficiency mode and is defined in a general way so it can be used for solving any collaborative vehicle routing problem. It consists of two subproblems, the Coalition Level Optimisation Problem (CLOP) and the Partner level Optimisation Problem (PLOP), which are solved sequentially. Both subproblems are linked through the definition of the acceptable region $\mathcal{R}$(CE), in which CE is the optimal solution of the CLOP.

With this thesis, we hope to have initiated a discussion on the requisites of collaborative logistics optimisation models. The models and frameworks proposed in this dissertation can be considered a first (important) step. The following opportunities for further research are identified. First, by considering both coalition objectives and partner objectives, all collaborative models are multi-objective. The inclusion of qualitative evaluation techniques to compare the solution space of multiple models and algorithms (e.g., the hypervolume, measure of spacing and spread,. . .) will help to score the quality of existing and new solutions approaches. Furthermore, by evaluating these metrics also during the optimisation procedure, the algorithmic performance can be tweaked. Second, we encourage the research community to focus especially on the interdependency between decision making at strategical, tactical and operational level. More specifically, further research should address how a decision of one partners (strategical, tactical or operational) influences the performance of the coalition and the position of this partner in the coalition. Finally, in all developed models no a-priori decision is made on the importance of the different objective functions in the model. As a result, not a single optimal solution but a set of Pareto-optimal solutions is obtained. The decision on which solution to prefer from this set will be based on a multi-criteria analysis, based on the partners' preferences. This decision was however out of the scope of this thesis and left for future research.

9.2 Recommendations to the industry

As supply chain cooperation is above all a people business, the success of each initiative is highly dependent on the persons around the table. This makes it highly difficult to define global best practices, and the need for a case-by-case approach is often acknowledged. However, based on the research results presented in this dissertation, we were able to formulate the following recommendations.

We showed that the efficiency of the collaborative operational plan is highly dependent on the commitment of each individual partner. More specifically, their willingness to disregard their own priorities and objectives and the degree to which each company allows a shift in decision-making towards the benefit of the coalition largely determines the possible synergy obtained by the coalition. We identified the cost allocation mechanism as a suitable tool to provide the necessary incentives to the individual partners to alter their behaviour and adopts a more flexible attitude. As we showed that significant differences exist between different allocation methods, this decision should be taken with caution on a case-based approach.

One of the results of this thesis is also that the most optimal solution for the coalition is often not the best result for the individual partners. When engaging in a cooperation, companies should therefore be aware of the impact of decisions at the coalition level (allocation rules, operational decisions, . . .) on their personal objectives. Furthermore, although individual partner objectives might be the same for different partners (e.g. minimisation of the total logistics cost), each partner might prefer other operational decisions to achieve his personal goal. Again, this impact is largely determined by the negotiated allocation rules to project the realisations of the group to the individual partners.

To conclude we can state that the success of a cooperation is largely determined by the people around the table and trust among the coalition members. From the moment that the coalition should take a decision about two alternative solutions (multiple possible allocation rules, a change in the operational plan,. . .), it is likely that a benefit for one partner results in a loss for the other. Finding the right balance depends not only on mathematical properties of fairness, but also on negotiation, compromises, and other intangible assets that are difficult (or even impossible) to capture in formulas and equations. Therefore, I recommend companies to choose for straightforward, easy and predictable methods and rules rather than complex cooperative game theoretical concepts to support their decision-making process.

Part V

APPENDIX

10

Detailed results for the CLUVRP

Abstract:

This chapter contains the detailed results from the simulation experiments conducted in chapter 7 of this thesis.

Table 10.1: Detailed results for the GVRPθ3 instances A, B.

						Strong cluster constraint				Weak cluster constraints	
		instance					GAP(%)		CPU(s)	GAP(%)	
set	n	k	c	v	opt.	Best	Avg. best	Avg.	Avg.	Avg. Best	Avg.
A	32	5	11	2	522	**522**	**0.00%**	**0.00%**	0.00	-1.34%	-1.34%
A	33	5	11	2	472	**472**	**0.00%**	**0.00%**	0.00	-2.33%	-2.33%
A	33	6	11	2	562	**562**	**0.00%**	**0.00%**	0.00	-1.42%	-1.42%
A	34	5	12	2	547	**547**	**0.00%**	**0.00%**	0.00	-1.65%	-1.65%
A	36	5	12	2	588	589	0.17%	0.17%	0.00	-7.81%	-7.81%
A	37	5	13	2	569	**569**	**0.00%**	**0.00%**	0.00	-2.46%	-2.46%
A	37	6	13	2	615	**615**	**0.00%**	**0.00%**	0.02	-1.63%	-1.56%
A	38	5	13	2	507	**507**	**0.00%**	**0.00%**	0.00	0.00%	0.00%
A	39	5	13	2	610	**610**	**0.00%**	**0.00%**	0.02	-3.61%	-3.41%
A	39	6	13	2	613	**613**	**0.00%**	**0.00%**	0.00	-1.63%	-1.63%
A	44	6	15	2	714	**714**	**0.00%**	**0.00%**	0.04	-3.22%	-3.22%
A	45	6	15	3	712	**712**	**0.00%**	**0.00%**	0.00	-8.43%	-8.43%
A	45	7	15	3	664	**664**	**0.00%**	**0.00%**	0.00	-0.45%	-0.45%
A	46	7	16	3	664	**664**	**0.00%**	**0.00%**	0.00	-3.31%	-3.31%
A	48	7	16	3	683	**683**	**0.00%**	**0.00%**	0.00	-0.44%	-0.44%
A	53	7	18	3	651	**651**	**0.00%**	**0.00%**	0.00	-3.69%	-3.69%
A	54	7	18	3	724	**724**	**0.00%**	**0.00%**	0.01	-3.45%	-3.45%
A	55	9	19	3	653	**653**	**0.00%**	**0.00%**	0.00	-1.23%	-1.23%
A	60	9	20	3	787	795	1.02%	1.02%	0.02	-4.15%	-4.04%
A	61	9	21	4	682	**682**	**0.00%**	**0.00%**	0.00	-1.61%	-1.11%
A	62	8	21	3	778	**778**	**0.00%**	**0.00%**	0.01	-0.90%	-0.90%
A	63	10	21	4	801	**801**	**0.00%**	**0.00%**	0.02	-2.75%	-2.65%
A	63	9	21	3	865	**865**	**0.00%**	**0.00%**	0.45	-3.24%	-3.21%
A	64	9	22	3	773	**773**	**0.00%**	**0.00%**	0.09	-0.78%	-0.78%
A	65	9	22	3	725	**725**	**0.00%**	0.01%	0.15	-4.41%	-4.41%
A	69	9	23	3	814	819	0.61%	0.66%	0.38	-3.05%	-2.37%
A	80	10	27	4	972	**972**	**0.00%**	0.10%	0.27	-2.88%	-2.78%
B	31	5	11	2	375	**375**	**0.00%**	**0.00%**	0.00	0.00%	0.00%
B	34	5	12	2	416	**416**	**0.00%**	**0.00%**	0.00	-0.24%	-0.24%
B	35	5	12	2	562	**562**	**0.00%**	0.16%	0.03	-0.89%	-0.89%
B	38	6	13	2	431	**431**	**0.00%**	**0.00%**	0.06	-0.93%	-0.93%
B	39	5	13	2	321	**321**	**0.00%**	**0.00%**	0.00	-1.25%	-1.25%
B	41	6	14	2	476	**476**	**0.00%**	**0.00%**	0.00	-1.47%	-1.47%
B	43	6	15	2	415	**415**	**0.00%**	**0.00%**	0.00	-2.41%	-2.41%
B	44	7	15	3	447	**447**	**0.00%**	**0.00%**	0.00	-0.89%	-0.89%
B	45	5	15	2	506	508	0.40%	0.41%	0.02	-3.74%	-3.74%
B	45	6	15	2	391	**391**	**0.00%**	**0.00%**	0.02	-1.28%	-1.28%
B	50	7	17	3	467	**467**	**0.00%**	**0.00%**	0.00	-0.64%	-0.64%
B	50	8	17	3	666	**666**	**0.00%**	**0.00%**	0.02	-0.75%	-0.75%
B	51	7	17	3	585	**585**	**0.00%**	**0.00%**	0.00	-1.20%	-1.20%
B	52	7	18	3	427	**427**	**0.00%**	**0.00%**	0.00	0.00%	0.00%
B	56	7	19	3	433	434	0.23%	0.23%	0.01	-3.23%	-3.23%
B	57	7	19	3	634	**634**	**0.00%**	**0.00%**	0.01	-1.89%	-1.89%
B	57	9	19	3	753	**753**	**0.00%**	**0.00%**	0.01	-0.93%	-0.93%
B	63	10	21	3	685	**685**	**0.00%**	**0.00%**	0.06	0.00%	0.00%
B	64	9	22	4	526	**526**	**0.00%**	**0.00%**	0.00	-0.38%	-0.38%
B	66	9	22	3	687	**687**	**0.00%**	**0.00%**	0.26	-0.58%	-0.58%
B	67	10	23	4	626	**626**	**0.00%**	**0.00%**	0.04	-1.12%	-1.12%
B	68	9	23	3	588	**588**	**0.00%**	0.03%	0.29	-1.02%	-1.02%
B	78	10	26	4	721	**721**	**0.00%**	**0.00%**	0.02	-2.36%	-2.36%

Table 10.2: Detailed results for the GVRPθ3 instances G, M, P.

						Strong cluster constraint				Weak cluster constraints	
instance							GAP(%)		CPU(s)	GAP(%)	
set	n	k	c	v	opt.	Best	Avg. best	Avg.	Avg.	Avg. Best	Avg.
G	262	25	88	9	-	**3310**			15.95	-3.44%	-2.71%
M	101	10	34	4	607	**607**	**0.00%**	**0.00%**	0.03	-1.48%	-1.48%
M	121	7	41	3	691	**691**	**0.00%**	0.35%	4.25	-1.45%	-0.94%
M	151	12	51	4	804	805	0.12%	0.19%	3.20	-5.71%	-5.11%
M	200	16	67	6	914 (UB)	**909**	**-0.55%**	**-0.34%**	6.45	-3.85%	-3.40%
P	101	4	34	2	679	**679**	**0.00%**	**0.00%**	0.20	-4.42%	-4.32%
P	16	8	6	4	253	**253**	**0.00%**	**0.00%**	0.00	-0.79%	-0.79%
P	19	2	7	1	186	**186**	**0.00%**	**0.00%**	0.00	-8.60%	-8.60%
P	20	2	7	1	200	**200**	**0.00%**	**0.00%**	0.00	-11.50%	-11.50%
P	21	2	7	1	190	**190**	**0.00%**	**0.00%**	0.00	-5.79%	-5.79%
P	22	2	8	1	202	**202**	**0.00%**	**0.00%**	0.00	-9.41%	-9.41%
P	22	8	8	4	365	**365**	**0.00%**	**0.00%**	0.00	0.00%	0.00%
P	23	8	8	3	279	**279**	**0.00%**	**0.00%**	0.00	-3.23%	-3.23%
P	40	5	14	2	396	**396**	**0.00%**	**0.00%**	0.00	-3.79%	-3.79%
P	45	5	15	2	440	**440**	**0.00%**	**0.00%**	0.00	-4.09%	-4.09%
P	50	10	17	4	491	**491**	**0.00%**	**0.00%**	0.02	-4.07%	-4.07%
P	50	7	17	3	447	**447**	**0.00%**	**0.00%**	0.02	-3.80%	-3.80%
P	50	8	17	3	460	**460**	**0.00%**	**0.00%**	0.01	-4.13%	-4.13%
P	51	10	17	4	537	**537**	**0.00%**	0.02%	0.03	-8.19%	-8.19%
P	55	10	19	4	500	**500**	**0.00%**	**0.00%**	0.03	-3.80%	-3.75%
P	55	15	19	6	595	**595**	**0.00%**	**0.00%**	0.01	-3.87%	-3.87%
P	55	7	19	3	462	**462**	**0.00%**	**0.00%**	0.00	-1.30%	-1.30%
P	55	8	19	3	471	**471**	**0.00%**	**0.00%**	0.02	-3.18%	-3.18%
P	60	10	20	4	552	**552**	**0.00%**	0.03%	0.19	-3.08%	-2.96%
P	60	15	20	5	611	**611**	**0.00%**	0.18%	0.29	-3.27%	-3.27%
P	65	10	22	4	619	**619**	**0.00%**	**0.00%**	0.01	-5.98%	-5.98%
P	70	10	24	4	643	644	0.16%	0.16%	0.01	-6.52%	-6.12%
P	76	4	26	2	581	**581**	**0.00%**	**0.00%**	0.41	-4.13%	-3.81%
P	76	5	26	2	581	**581**	**0.00%**	**0.00%**	0.31	-4.30%	-4.00%

Table 10.3: Detailed results for the Golden instances 1 – 5, as provided by Battarra, Erdoğan, and Vigo (2014).

				Strong cluster constraint				Weak cluster constraints	
	instance				GAP(%)		CPU(s)	GAP(%)	
set	n	N	opt.	Best	Avg. best	Avg.	Avg.	Best	Avg.
Golden-1	241	17	4831	4862	0.64%	1.19%	5.33	-3.39%	-2.38%
Golden-1	241	18	4847	4864	0.35%	0.98%	4.68	-2.80%	-1.97%
Golden-1	241	19	4872	4889	0.35%	1.24%	4.05	-2.92%	-2.41%
Golden-1	241	21	4889	4914	0.51%	1.13%	5.65	-2.81%	-2.43%
Golden-1	241	22	4908	4950	0.86%	1.20%	4.07	-4.36%	-3.21%
Golden-1	241	25	4899	4917	0.37%	0.80%	3.72	-3.72%	-3.21%
Golden-1	241	27	4934	4952	0.36%	0.67%	4.14	-4.81%	-3.70%
Golden-1	241	31	5050	5053	0.06%	0.19%	5.21	-5.68%	-4.99%
Golden-1	241	35	5102	5116	0.27%	0.54%	4.75	-7.74%	-6.81%
Golden-1	241	41	5097	5113	0.31%	0.74%	4.85	-7.88%	-6.76%
Golden-1	241	49	5000	5039	0.78%	1.35%	4.24	-7.32%	-5.43%
Golden-2	321	22	7716	7785	0.89%	1.24%	6.19	-2.84%	-2.43%
Golden-2	321	23	7693	7768	0.97%	1.36%	5.29	-2.79%	-2.43%
Golden-2	321	25	7668	7728	0.78%	1.15%	5.79	-3.35%	-2.44%
Golden-2	321	27	7638	7705	0.88%	1.23%	4.50	-2.92%	-2.39%
Golden-2	321	30	7617	7689	0.95%	1.51%	5.51	-2.65%	-2.26%
Golden-2	321	33	7640	7705	0.85%	1.24%	4.84	-3.04%	-2.70%
Golden-2	321	36	7643	7699	0.73%	1.14%	3.62	-3.27%	-2.79%
Golden-2	321	41	7738	7781	0.56%	1.16%	5.08	-4.25%	-3.46%
Golden-2	321	46	7861	7926	0.83%	1.30%	4.43	-5.41%	-4.86%
Golden-2	321	54	7920	7989	0.87%	1.28%	3.84	-6.28%	-5.62%
Golden-2	321	65	7892	7997	1.33%	1.71%	5.45	-6.50%	-5.67%
Golden-3	401	27	10540	10662	1.16%	1.80%	4.81	-2.56%	-2.17%
Golden-3	401	29	10504	10627	1.17%	1.50%	5.33	-3.72%	-2.92%
Golden-3	401	31	10486	10616	1.24%	1.48%	4.68	-3.23%	-2.79%
Golden-3	401	34	10465	10602	1.31%	1.64%	5.18	-2.92%	-2.60%
Golden-3	401	37	10482	10605	1.17%	1.66%	4.25	-3.30%	-2.75%
Golden-3	401	41	10501	10606	1.00%	1.51%	4.87	-3.12%	-2.70%
Golden-3	401	45	10485	10649	1.56%	1.78%	4.56	-3.73%	-2.98%
Golden-3	401	51	10583	10722	1.31%	2.00%	4.46	-4.01%	-3.43%
Golden-3	401	58	10776	10905	1.20%	1.71%	4.75	-5.09%	-4.48%
Golden-3	401	67	10797	10953	1.44%	1.79%	4.51	-6.06%	-4.96%
Golden-3	401	81	10614	10756	1.34%	1.91%	4.96	-4.14%	-3.44%
Golden-4	481	33	13598	13805	1.52%	1.99%	5.07	-4.97%	-3.95%
Golden-4	481	35	13643	13795	1.11%	1.89%	4.35	-4.28%	-3.71%
Golden-4	481	37	13520	13722	1.49%	1.83%	5.32	-4.59%	-3.80%
Golden-4	481	41	13460	13618	1.17%	1.91%	5.09	-4.46%	-3.52%
Golden-4	481	44	13568	13756	1.39%	1.70%	5.25	-4.66%	-3.97%
Golden-4	481	49	13758	13968	1.53%	2.10%	4.93	-5.98%	-5.19%
Golden-4	481	54	13760	13985	1.64%	2.27%	5.62	-6.16%	-5.02%
Golden-4	481	61	13791	14045	1.84%	2.25%	5.51	-6.09%	-4.98%
Golden-4	481	69	13966	14143	1.27%	2.00%	4.31	-6.00%	-5.35%
Golden-4	481	81	13975	14167	1.37%	2.13%	5.32	-6.58%	-5.75%
Golden-4	481	97	13775	13973	1.44%	2.22%	3.50	-4.46%	-3.96%
Golden-5	201	14	7622	7652	0.39%	0.74%	4.62	-7.08%	-6.39%
Golden-5	201	15	7424	7429	0.07%	0.67%	4.52	-8.49%	-7.55%
Golden-5	201	16	7491	**7491**	**0.00%**	0.30%	4.89	-8.92%	-8.00%
Golden-5	201	17	7434	**7434**	**0.00%**	0.44%	4.81	-7.61%	-7.04%
Golden-5	201	19	7576	**7576**	**0.00%**	0.08%	4.14	-7.23%	-6.69%
Golden-5	201	21	7596	**7596**	**0.00%**	0.03%	4.59	-9.00%	-8.39%
Golden-5	201	23	7643	**7643**	**0.00%**	0.24%	2.38	-11.33%	-10.18%
Golden-5	201	26	7560	7566	0.08%	0.21%	3.66	-11.12%	-10.20%
Golden-5	201	29	7410	**7410**	**0.00%**	0.04%	4.91	-8.99%	-8.11%
Golden-5	201	34	7429	7433	0.05%	0.17%	5.28	-9.66%	-8.32%
Golden-5	201	41	7241	7251	0.14%	0.25%	5.39	-9.20%	-8.11%

Table 10.4: Detailed results for the Golden instances 6 – 10, as provided by Battarra, Erdoğan, and Vigo (2014).

				Strong cluster constraint				Weak cluster constraints	
instance					GAP(%)		CPU(s)	GAP(%)	
set	n	N	opt.	Best	Avg. best	Avg.	Avg.	Best	Avg.
Golden-6	281	19	8624	8685	0.71%	0.94%	4.72	-5.62%	-4.91%
Golden-6	281	21	8628	8661	0.38%	0.73%	5.04	-5.83%	-4.38%
Golden-6	281	22	8646	8715	0.80%	1.26%	6.02	-5.96%	-4.67%
Golden-6	281	24	8853	8905	0.59%	1.04%	3.59	-5.44%	-4.63%
Golden-6	281	26	8910	8978	0.76%	1.31%	4.16	-6.32%	-5.52%
Golden-6	281	29	8936	9025	1.00%	1.46%	4.69	-6.98%	-6.08%
Golden-6	281	32	8891	8974	0.93%	1.44%	3.93	-7.62%	-5.90%
Golden-6	281	36	8969	9011	0.47%	0.82%	4.89	-6.97%	-6.36%
Golden-6	281	41	9028	9067	0.43%	0.80%	5.37	-7.30%	-6.42%
Golden-6	281	47	8923	8996	0.82%	1.37%	2.99	-7.19%	-6.10%
Golden-6	281	57	9028	9107	0.88%	1.32%	5.36	-7.09%	-6.23%
Golden-7	361	25	9904	10021	1.18%	1.68%	4.32	-4.42%	-3.72%
Golden-7	361	26	9888	10023	1.37%	1.76%	5.61	-4.42%	-3.71%
Golden-7	361	28	9917	10056	1.40%	1.84%	5.39	-4.72%	-4.02%
Golden-7	361	31	10021	10131	1.10%	1.53%	4.67	-3.99%	-3.58%
Golden-7	361	33	10029	10161	1.32%	1.57%	5.07	-4.68%	-4.02%
Golden-7	361	37	10131	10176	0.44%	1.14%	4.67	-4.93%	-3.75%
Golden-7	361	41	10052	10119	0.67%	1.27%	4.94	-4.50%	-3.61%
Golden-7	361	46	10080	10197	1.16%	1.77%	5.75	-5.44%	-4.24%
Golden-7	361	52	10095	10201	1.05%	1.61%	4.40	-4.97%	-4.10%
Golden-7	361	61	10096	10189	0.92%	1.74%	5.74	-4.67%	-4.18%
Golden-7	361	73	10014	10095	0.81%	1.52%	4.70	-4.88%	-3.57%
Golden-8	441	30	10866	11002	1.25%	1.58%	4.86	-3.19%	-2.45%
Golden-8	441	32	10831	10943	1.03%	1.73%	5.82	-2.77%	-2.07%
Golden-8	441	34	10847	10963	1.07%	1.68%	5.33	-2.56%	-2.04%
Golden-8	441	37	10859	11010	1.39%	1.95%	5.06	-3.18%	-2.59%
Golden-8	441	41	10934	11088	1.41%	1.79%	5.94	-3.57%	-3.02%
Golden-8	441	45	10960	11103	1.30%	1.60%	4.48	-3.93%	-3.00%
Golden-8	441	49	11042	11177	1.22%	1.61%	4.81	-3.98%	-3.34%
Golden-8	441	56	11194	11350	1.39%	1.86%	4.86	-5.50%	-4.48%
Golden-8	441	63	11252	11412	1.42%	1.76%	4.64	-5.83%	-4.51%
Golden-8	441	74	11321	11462	1.25%	2.09%	4.50	-6.17%	-4.84%
Golden-8	441	89	11209	11409	1.78%	2.45%	5.08	-6.09%	-4.74%
Golden-9	256	18	300	304	1.33%	1.77%	4.62	-5.26%	-4.18%
Golden-9	256	19	299	304	1.67%	1.96%	3.67	-5.59%	-3.98%
Golden-9	256	20	296	298	0.68%	1.59%	3.09	-3.69%	-2.67%
Golden-9	256	22	290	295	1.72%	2.45%	3.98	-3.39%	-2.85%
Golden-9	256	24	290	295	1.72%	2.48%	3.84	-3.73%	-2.78%
Golden-9	256	26	288	293	1.74%	2.20%	5.29	-3.41%	-2.92%
Golden-9	256	29	292	297	1.71%	2.40%	3.21	-5.39%	-4.09%
Golden-9	256	32	297	300	1.01%	1.58%	4.38	-6.67%	-5.02%
Golden-9	256	37	294	296	0.68%	1.55%	3.31	-5.41%	-3.89%
Golden-9	256	43	295	300	1.69%	2.36%	2.97	-6.33%	-5.27%
Golden-9	256	52	296	298	0.68%	2.50%	4.30	-6.38%	-5.05%
Golden-10	324	22	367	369	0.54%	1.20%	2.41	-3.25%	-1.88%
Golden-10	324	24	361	**361**	**0.00%**	0.43%	5.03	-1.94%	-0.83%
Golden-10	324	25	359	360	0.28%	0.88%	3.75	-1.11%	-0.58%
Golden-10	324	27	361	363	0.55%	1.65%	3.53	-1.65%	-1.17%
Golden-10	324	30	367	371	1.09%	1.58%	4.31	-3.77%	-2.87%
Golden-10	324	33	373	378	1.34%	2.25%	2.51	-5.82%	-4.80%
Golden-10	324	36	385	391	1.56%	2.04%	4.22	-8.70%	-7.43%
Golden-10	324	41	400	403	0.75%	1.44%	4.72	-9.93%	-9.09%
Golden-10	324	47	398	402	1.01%	1.58%	4.65	-10.45%	-9.38%
Golden-10	324	54	393	397	1.02%	1.95%	3.92	-10.08%	-8.66%
Golden-10	324	65	387	395	2.07%	2.70%	3.64	-10.38%	-8.09%

Table 10.5: Detailed results for the Golden instances 11 – 15, as provided by Battarra, Erdoğan, and Vigo (2014).

				Strong cluster constraint				Weak cluster constraints	
instance					GAP(%)		CPU(s)	GAP(%)	
set	n	N	opt.	Best	Avg. best	Avg.	Avg.	Best	Avg.
Golden-11	400	27	457	464	1.53%	1.76%	3.58	-3.66%	-2.73%
Golden-11	400	29	455	463	1.76%	2.38%	3.58	-3.46%	-2.71%
Golden-11	400	31	455	464	1.98%	2.59%	5.29	-3.66%	-2.66%
Golden-11	400	34	455	462	1.54%	2.21%	4.23	-4.55%	-3.19%
Golden-11	400	37	459	469	2.18%	2.68%	4.65	-5.33%	-4.08%
Golden-11	400	40	461	467	1.30%	2.25%	3.87	-4.93%	-3.88%
Golden-11	400	45	462	470	1.73%	2.54%	4.69	-5.96%	-4.66%
Golden-11	400	50	458	467	1.97%	2.90%	4.81	-5.35%	-3.74%
Golden-11	400	58	456	468	2.63%	3.30%	4.64	-4.91%	-3.84%
Golden-11	400	67	454	469	3.30%	4.13%	4.20	-4.90%	-3.57%
Golden-11	400	80	451	468	3.77%	4.71%	3.87	-4.70%	-3.26%
Golden-12	484	33	535	545	1.87%	2.50%	4.38	-2.94%	-1.59%
Golden-12	484	35	537	547	1.86%	2.50%	3.40	-2.93%	-1.86%
Golden-12	484	38	535	547	2.24%	3.39%	4.15	-2.93%	-1.37%
Golden-12	484	41	537	550	2.42%	3.66%	3.67	-3.27%	-1.87%
Golden-12	484	44	535	552	3.18%	4.02%	4.11	-3.99%	-2.23%
Golden-12	484	49	533	550	3.19%	3.96%	4.01	-2.00%	-1.09%
Golden-12	484	54	535	551	2.99%	3.83%	4.74	-2.54%	-1.11%
Golden-12	484	61	538	552	2.60%	3.67%	4.16	-2.36%	-1.24%
Golden-12	484	70	546	552	1.10%	1.83%	3.76	-2.54%	-1.19%
Golden-12	484	81	546	557	2.01%	2.79%	4.52	-3.23%	-1.71%
Golden-12	484	97	560	566	1.07%	2.07%	3.98	-3.89%	-2.71%
Golden-13	253	17	552	553	0.18%	0.57%	4.43	-2.71%	-1.98%
Golden-13	253	19	549	552	0.55%	0.77%	4.79	-3.99%	-3.28%
Golden-13	253	20	548	549	0.18%	0.60%	4.84	-3.28%	-2.98%
Golden-13	253	22	548	549	0.18%	0.74%	2.80	-3.46%	-2.86%
Golden-13	253	23	548	551	0.55%	0.78%	3.73	-3.99%	-3.42%
Golden-13	253	26	542	544	0.37%	0.62%	3.69	-2.76%	-2.30%
Golden-13	253	29	540	543	0.56%	0.77%	3.64	-2.58%	-2.00%
Golden-13	253	32	543	545	0.37%	0.69%	4.75	-2.94%	-2.19%
Golden-13	253	37	545	550	0.92%	1.21%	3.84	-3.45%	-2.84%
Golden-13	253	43	553	559	1.08%	1.52%	3.24	-4.83%	-4.43%
Golden-13	253	51	560	565	0.89%	1.44%	3.90	-5.84%	-5.13%
Golden-14	321	22	692	698	0.87%	1.23%	4.23	-2.72%	-2.25%
Golden-14	321	23	688	692	0.58%	1.02%	4.27	-2.46%	-2.08%
Golden-14	321	25	678	683	0.74%	1.07%	3.87	-2.05%	-1.46%
Golden-14	321	27	676	683	1.04%	1.45%	4.35	-1.90%	-1.62%
Golden-14	321	30	678	684	0.88%	1.47%	3.94	-2.05%	-1.62%
Golden-14	321	33	682	687	0.73%	1.20%	3.68	-2.18%	-1.94%
Golden-14	321	36	687	689	0.29%	1.16%	3.35	-3.05%	-2.26%
Golden-14	321	41	690	695	0.72%	1.17%	5.46	-3.88%	-2.93%
Golden-14	321	46	694	699	0.72%	1.44%	3.99	-3.29%	-2.72%
Golden-14	321	54	699	706	1.00%	1.58%	3.83	-4.53%	-3.46%
Golden-14	321	65	703	713	1.42%	1.74%	3.55	-4.77%	-4.03%
Golden-15	397	27	842	850	0.95%	1.53%	5.14	-2.94%	-2.01%
Golden-15	397	29	843	854	1.30%	1.64%	5.01	-3.40%	-2.51%
Golden-15	397	31	837	846	1.08%	1.62%	4.64	-2.36%	-1.59%
Golden-15	397	34	838	851	1.55%	2.05%	3.95	-2.94%	-2.30%
Golden-15	397	37	845	858	1.54%	1.99%	4.09	-3.73%	-3.01%
Golden-15	397	40	849	859	1.18%	1.60%	2.90	-3.38%	-2.81%
Golden-15	397	45	853	864	1.29%	1.50%	4.39	-3.47%	-2.80%
Golden-15	397	50	851	863	1.41%	1.77%	3.04	-2.78%	-2.47%
Golden-15	397	57	850	859	1.06%	1.84%	3.98	-2.44%	-1.82%
Golden-15	397	67	855	870	1.75%	2.26%	3.74	-3.45%	-2.55%
Golden-15	397	80	857	874	1.98%	2.51%	3.32	-3.55%	-2.64%

Table 10.6: Detailed results for the Golden instances 16 – 20, as provided by Battarra, Erdoğan, and Vigo (2014).

				Strong cluster constraint				Weak cluster constraints	
instance					GAP(%)		CPU(s)	GAP(%)	
set	n	N	opt.	Best	Avg. best	Avg.	Avg.	Best	Avg.
Golden-16	481	35	1028	1038	0.97%	1.31%	4.24	-2.60%	-1.89%
Golden-16	481	37	1028	1037	0.88%	1.21%	3.66	-2.89%	-1.96%
Golden-16	481	41	1032	1039	0.68%	1.31%	4.43	-2.50%	-1.74%
Golden-16	481	44	1028	1042	1.36%	1.71%	4.53	-2.30%	-1.77%
Golden-16	481	49	1031	1044	1.26%	1.66%	5.56	-2.87%	-2.20%
Golden-16	481	54	1022	1038	1.57%	1.91%	4.39	-2.50%	-2.13%
Golden-16	481	61	1013	1035	2.17%	2.58%	3.85	-2.22%	-1.74%
Golden-16	481	69	1012	1035	2.27%	2.60%	3.86	-2.03%	-1.65%
Golden-16	481	81	1018	1043	2.46%	3.06%	2.93	-2.49%	-1.62%
Golden-16	481	97	1018	1048	2.95%	3.47%	3.16	-2.48%	-1.72%
Golden-17	241	17	418	421	0.72%	1.16%	3.44	-7.13%	-6.48%
Golden-17	241	18	419	421	0.48%	0.95%	2.77	-6.89%	-6.41%
Golden-17	241	19	422	424	0.47%	0.78%	5.01	-7.55%	-7.09%
Golden-17	241	21	425	427	0.47%	0.91%	3.68	-8.67%	-7.85%
Golden-17	241	22	424	426	0.47%	0.91%	4.59	-8.22%	-7.69%
Golden-17	241	25	418	421	0.72%	1.04%	3.70	-7.84%	-7.54%
Golden-17	241	27	414	416	0.48%	0.79%	2.29	-7.21%	-6.36%
Golden-17	241	31	421	422	0.24%	0.61%	2.33	-5.45%	-4.62%
Golden-17	241	35	417	418	0.24%	0.49%	3.34	-4.55%	-4.04%
Golden-17	241	41	412	**412**	**0.00%**	0.39%	4.96	-3.40%	-2.71%
Golden-17	241	49	414	416	0.48%	0.79%	3.45	-4.81%	-4.07%
Golden-18	301	21	592	599	1.18%	1.60%	4.13	-4.34%	-3.06%
Golden-18	301	22	594	602	1.35%	1.61%	4.89	-3.99%	-3.47%
Golden-18	301	24	592	601	1.52%	1.73%	5.09	-4.49%	-3.23%
Golden-18	301	26	590	595	0.85%	1.54%	3.41	-3.19%	-2.31%
Golden-18	301	28	577	582	0.87%	1.33%	4.42	-2.23%	-1.65%
Golden-18	301	31	578	583	0.87%	1.18%	4.09	-2.92%	-2.04%
Golden-18	301	34	582	585	0.52%	1.05%	4.38	-2.91%	-2.56%
Golden-18	301	38	586	592	1.02%	1.48%	2.32	-3.89%	-3.45%
Golden-18	301	43	594	599	0.84%	1.33%	4.50	-4.34%	-3.80%
Golden-18	301	51	601	605	0.67%	1.18%	3.29	-4.96%	-4.45%
Golden-18	301	61	599	602	0.50%	1.17%	3.73	-4.65%	-4.01%
Golden-19	361	25	925	936	1.19%	1.55%	5.06	-3.85%	-3.16%
Golden-19	361	26	924	935	1.19%	1.63%	4.84	-3.21%	-2.84%
Golden-19	361	28	808	818	1.24%	1.63%	4.36	-6.60%	-5.79%
Golden-19	361	31	811	822	1.36%	1.61%	4.41	-7.30%	-6.65%
Golden-19	361	33	797	806	1.13%	1.66%	4.96	-6.58%	-6.18%
Golden-19	361	37	799	809	1.25%	1.55%	4.51	-6.30%	-5.77%
Golden-19	361	41	789	796	0.89%	1.27%	4.03	-5.40%	-4.79%
Golden-19	361	46	788	794	0.76%	1.08%	3.13	-5.29%	-4.38%
Golden-19	361	52	800	807	0.88%	1.30%	3.43	-6.57%	-5.59%
Golden-19	361	61	807	812	0.62%	1.13%	3.09	-6.03%	-5.40%
Golden-19	361	73	810	814	0.49%	1.33%	3.00	-6.27%	-5.52%
Golden-20	421	29	1220	1231	0.90%	1.32%	4.78	-1.79%	-1.49%
Golden-20	421	31	1232	1239	0.57%	1.14%	4.30	-1.53%	-1.12%
Golden-20	421	33	1208	1219	0.91%	1.30%	4.37	-1.39%	-1.00%
Golden-20	421	36	1059	1073	1.32%	1.76%	5.44	-3.73%	-2.71%
Golden-20	421	39	1052	1063	1.05%	1.39%	5.13	-3.57%	-3.07%
Golden-20	421	43	1052	1062	0.95%	1.46%	3.37	-4.24%	-3.23%
Golden-20	421	47	1053	1065	1.14%	1.55%	3.90	-3.94%	-3.27%
Golden-20	421	53	1058	1071	1.23%	1.94%	3.41	-4.58%	-3.79%
Golden-20	421	61	1058	1072	1.32%	1.95%	3.82	-4.76%	-3.61%
Golden-20	421	71	1059	1076	1.61%	2.01%	2.80	-4.74%	-3.81%
Golden-20	421	85	1049	1062	1.24%	1.98%	4.38	-4.14%	-2.74%

11

Detailed results for the collaborative CLUVRP

Abstract:

This chapter contains the detailed results from the simulation experiments conducted in chapter 8 of this thesis.

Table 11.1: Detailed results for the two-partner COLGVRPθ3 instances with $\alpha = 0.01$.

instance					grand coalition			partner 1			partner 2			Pareto set	
n	k	C	V	p	total cost sa	total cost ce	max. profit	ce	profit min	profit max	ce	profit min	profit max	size	
32	5	11	2	2	634	522	18%	**15%**	15%	15%	**22%**	22%	22%	1	
33	5	11	2	2	578	472	18%	19%	19%	20%	**17%**	14%	17%	2	
33	6	11	2	2	676	562	17%	**24%**	24%	24%	**6%**	6%	6%	1	
34	5	12	2	2	651	547	16%	**25%**	23%	25%	5%	5%	7%	2	
36	5	12	2	2	746	589	21%	**26%**	26%	26%	**15%**	15%	15%	1	
37	5	13	2	2	677	569	16%	**17%**	17%	17%	**15%**	15%	15%	1	
37	6	13	2	2	733	615	16%	**21%**	21%	21%	**10%**	10%	10%	2	
38	5	13	2	2	692	507	27%	**37%**	37%	37%	**13%**	13%	13%	1	
39	5	13	2	2	751	618	18%	33%	33%	35%	**-1%**	-2%	-1%	3	
39	6	13	2	2	765	613	20%	**33%**	33%	33%	**0%**	0%	0%	1	
44	6	15	2	2	811	733	10%	**6%**	6%	6%	**12%**	12%	12%	1	
45	6	15	3	2	776	712	8%	**14%**	13%	14%	-2%	-2%	-1%	2	
45	7	15	3	2	818	664	19%	13%	13%	14%	**29%**	24%	29%	2	
46	7	16	3	2	801	664	17%	18%	18%	19%	**15%**	13%	15%	2	
48	7	16	3	2	836	683	18%	15%	15%	19%	**23%**	16%	23%	3	
53	7	18	3	2	817	651	20%	**17%**	17%	17%	**24%**	24%	24%	1	
54	7	18	3	2	873	724	17%	15%	15%	16%	**20%**	19%	20%	2	
55	9	19	3	2	795	653	18%	**14%**	14%	14%	**25%**	25%	25%	1	
60	9	20	3	2	904	795	12%	**8%**	8%	8%	19%	18%	21%	2	
61	9	21	4	2	832	682	18%	**26%**	25%	26%	**11%**	11%	11%	3	
62	8	21	3	2	910	778	15%	**12%**	12%	12%	**20%**	17%	20%	3	
63	9	21	3	2	1058	906	14%	**10%**	10%	10%	**23%**	23%	23%	1	
63	10	21	4	2	994	801	19%	**29%**	29%	29%	**10%**	9%	10%	2	
64	9	22	3	2	906	776	14%	**18%**	18%	18%	**8%**	8%	8%	1	
65	9	22	3	2	864	739	14%	**12%**	12%	12%	**18%**	18%	18%	1	
69	9	23	3	2	931	838	10%	2%	-4%	8%	22%	14%	32%	17	✗
80	10	27	4	2	1197	977	18%	**34%**	34%	34%	**1%**	1%	1%	1	

Table 11.2: Detailed results for the COLGVRPθ3 instances with more than two partners with $\alpha = 0.01$.

instance					grand coalition			partner 1			partner 2			partner 3			partner 4			Pareto set	
n	k	C	V	p	total cost sa	total cost ce	max. profit	ce	profit min	profit max	ce	profit min	profit max	ce	profit min	profit max	ce	profit min	profit max	size	
45	6	15	3	3	999	712	29%	**58%**	57%	58%	-2%	-2%	-1%	**14%**	13%	14%				2	
45	7	15	3	3	938	664	29%	31%	31%	36%	**29%**	24%	29%	**27%**	25%	27%				2	
46	7	16	3	3	947	664	30%	**55%**	53%	55%	**15%**	9%	15%	14%	14%	19%				4	
48	7	16	3	3	960	683	29%	**41%**	40%	41%	**23%**	20%	23%	22%	22%	25%				2	
53	7	18	3	3	986	651	34%	**46%**	46%	46%	**24%**	24%	24%	**32%**	32%	32%				1	
54	7	18	3	3	997	724	27%	**22%**	18%	22%	**20%**	19%	20%	43%	43%	51%				2	
55	9	19	3	3	998	653	35%	**44%**	44%	44%	**25%**	25%	25%	**33%**	32%	33%				2	
60	9	20	3	3	1051	795	24%	**29%**	28%	29%	19%	18%	21%	24%	23%	25%				3	
62	8	21	3	3	1050	778	26%	**38%**	38%	38%	**20%**	17%	20%	15%	15%	16%				3	
63	9	21	3	3	1076	895	17%	12%	6%	14%	**25%**	19%	25%	12%	6%	17%				21	
64	9	22	3	3	1101	795	28%	37%	33%	41%	7%	4%	14%	35%	27%	41%				26	✗
65	9	22	3	3	996	751	25%	38%	38%	40%	19%	20%	22%	12%	12%	17%				2	✗
69	9	23	3	3	1052	820	22%	**27%**	23%	27%	28%	23%	29%	9%	9%	17%				9	
61	9	21	4	4	1134	682	40%	**53%**	53%	53%	46%	45%	47%	**43%**	42%	43%	13%	12%	14%	6	
63	10	21	4	4	1217	801	34%	**54%**	53%	54%	30%	30%	31%	**13%**	10%	13%	32%	32%	33%	2	

Table 11.3: Detailed results for the two-partner COLGVRPθ3 instances with $\alpha = 0.1$.

instance					grand coalition			partner 1			partner 2			Pareto set	
					total cost		max.		profit			profit			
n	**k**	**C**	**V**	**p**	**sa**	**ce**	**profit**	**ce**	**min**	**max**	**ce**	**min**	**max**	**size**	
32	5	11	2	2	634	522	18%	**15%**	15%	15%	**22%**	22%	22%	1	
33	5	11	2	2	578	472	18%	19%	5%	20%	17%	14%	22%	5	✗
33	6	11	2	2	676	562	17%	24%	16%	27%	6%	-10%	16%	5	✗
34	5	12	2	2	651	547	16%	**25%**	23%	25%	5%	5%	7%	2	
36	5	12	2	2	746	589	21%	**26%**	26%	26%	**15%**	15%	15%	1	
37	5	13	2	2	677	569	16%	17%	17%	18%	**15%**	2%	15%	3	
37	6	13	2	2	733	615	16%	21%	21%	23%	**10%**	6%	10%	3	
38	5	13	2	2	692	507	27%	**37%**	22%	37%	13%	13%	16%	4	
39	5	13	2	2	751	618	18%	33%	13%	35%	-1%	-2%	7%	9	✗
39	6	13	2	2	765	613	20%	**33%**	33%	33%	**0%**	-5%	0%	2	
44	6	15	2	2	811	729	10%	**-1%**	-1%	-1%	**19%**	19%	19%	1	
45	6	15	3	2	776	712	8%	14%	-8%	16%	-2%	-9%	12%	10	✗
45	7	15	3	2	818	664	19%	13%	13%	16%	**29%**	7%	29%	4	
46	7	16	3	2	801	664	17%	18%	16%	22%	15%	6%	16%	7	✗
48	7	16	3	2	836	683	18%	15%	15%	19%	**23%**	9%	23%	4	
53	7	18	3	2	817	651	20%	17%	7%	21%	24%	16%	25%	9	✗
54	7	18	3	2	873	724	17%	15%	-4%	16%	20%	13%	30%	19	✗
55	9	19	3	2	795	653	18%	**14%**	11%	14%	**25%**	25%	25%	2	
60	9	20	3	2	904	795	12%	**8%**	-5%	8%	19%	18%	22%	11	
61	9	21	4	2	832	682	18%	**26%**	15%	26%	11%	11%	14%	6	
62	8	21	3	2	910	778	15%	12%	8%	13%	**20%**	11%	20%	6	
63	9	21	3	2	1029	865	16%	10%	0%	13%	26%	2%	29%	12	✗
63	10	21	4	2	994	801	19%	**29%**	10%	29%	10%	1%	13%	5	
64	9	22	3	2	906	776	14%	**18%**	3%	18%	8%	8%	15%	9	
65	9	22	3	2	839	749	11%	6%	8%	8%	18%	22%	22%	1	✗
69	9	23	3	2	931	839	10%	1%	-5%	12%	23%	9%	31%	17	✗
80	10	27	4	2	1197	976	18%	35%	16%	38%	0%	-7%	9%	28	✗

Table 11.4: Detailed results for the COLGVRPθ3 instances with more than two partners with $\alpha = 0.1$.

instance					grand coalition			partner 1			partner 2			partner 3			partner 4			Pareto set	
n	k	C	V	p	total cost sa	total cost ce	max. profit	ce	profit min	profit max	ce	profit min	profit max	ce	profit min	profit max	ce	profit min	profit max	size	
45	6	15	3	3	999	712	29%	58%	27%	60%	-2%	-31%	12%	14%	-7%	27%				71	✗
45	7	15	3	3	938	664	29%	31%	26%	38%	**29%**	7%	29%	27%	13%	30%				20	
46	7	16	3	3	947	664	30%	55%	34%	57%	15%	-11%	20%	14%	-5%	27%				68	✗
48	7	16	3	3	960	683	29%	41%	26%	43%	23%	3%	24%	22%	10%	33%				39	✗
53	7	18	3	3	986	651	34%	46%	32%	49%	24%	9%	26%	32%	25%	42%				46	✗
54	7	18	3	3	997	724	27%	22%	0%	26%	20%	0%	30%	43%	22%	51%				33	✗
55	9	19	3	3	998	653	35%	**44%**	42%	44%	25%	25%	26%	**33%**	25%	33%				5	
60	9	20	3	3	1051	795	24%	**29%**	26%	29%	19%	18%	22%	24%	22%	25%				10	
62	8	21	3	3	1050	778	26%	38%	21%	39%	**20%**	0%	20%	15%	11%	23%				57	
63	9	21	3	3	1076	909	16%	12%	-5%	20%	15%	-3%	28%	19%	-1%	26%				70	✗
64	9	22	3	3	1101	785	29%	37%	18%	45%	8%	-22%	17%	37%	10%	47%				217	✗
65	9	22	3	3	996	726	27%	39%	33%	40%	**22%**	5%	22%	17%	12%	20%				6	
69	9	23	3	3	1052	820	22%	27%	4%	29%	28%	10%	34%	9%	-10%	20%				69	✗
61	9	21	4	4	1134	682	40%	53%	36%	58%	46%	22%	49%	43%	17%	48%	13%	-12%	27%	404	✗
63	10	21	4	4	1217	801	34%	**54%**	34%	54%	30%	17%	32%	13%	1%	21%	32%	15%	34%	18	

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Notation

General

SYMBOL	MEANING
N	grand coalition
$\|N\|$ or n	number of partners in the grand coalition
S	subcoalition ($S \subseteq N$)

Cost allocation and gain sharing

SYMBOL	MEANING
Ψ	set of all possible cost allocations
Ψ_{IR}	set of all individual rational cost allocations ($\Psi_{IR} \subseteq \Psi$)
ψ	cost allocation result
ψ_i	cost allocated to partner i
$v(S)$	worth of subcoalition S
$c(S)$	cost of subcoalition S
$c(i)$	stand-alone cost of partner i
m_i	marginal cost of partner i
e_i	cost excess of cost allocation for partner i

The selective vehicle routing problem

SYMBOL	MEANING
K	set of vehicles
D	fixed maximum vehicle distance
c	number of customers
c_i^p	customer i, belonging to partner p
d_{ij}	travel cost between customers i and j
u_{ik}	position of vertex i in the route of vehicle k
CND_i	compensation for non-delivery of customer i
$\sum_p \text{CND}_{p,\text{sol}}$	total CND of the customers of partner p in the solution
m_i	marginal cost of adding customer i in the current solution
M_p	sum of the marginal costs for every customer of partner p in the current solution

The clustered vehicle routing problem

SYMBOL	MEANING
V	set of vertices
E	set of edges
R	set of clusters
C_r	set of customers in cluster r
K	set of homogeneous vehicles
Q	vehicle capacity
d_{ij}	distance associated with edge $(i, j) \in E$
q_i	demand of customer i

Integrated solution framework

SYMBOL	MEANING
ζ	solution space
x	solution vector
$\mathcal{N}(x)$	the neighbourhood of solution vector x
K^c	set of vehicle at the coalition level
V^c	set of customers at the coalition level
K^p	set of vehicles of partner p
V^p	set of customers of partner p
$F_c(x)$	coalition objective
$F_i(x)$	partner objective
$d(a, b)$	distance between solution vectors a and b
ϵ	allowed distance between two solution vectors
SA	stand-alone solution
CE	coalition efficient solution
Ω	set of all cluster configurations
ω	cluster configuration

Acronyms

ACAM	Alternative Cost Avoided Method
CLOP	Coalition Level Optimisation Problem
CLUTSP	Clustered Travelling Salesman Problem
CLUVRP	Clustered Vehicle Routing Problem
CND	compensation for non-delivery
CPFR	Cooperative Planning, Forecasting and Replenishment
CVRP	Capacitated Vehicle Routing Problem
EPM	Equal Profit Method
FTL	Full Truckload
GRASP	Greedy Randomized Adaptive Search Procedure
GVRP	Generalised Vehicle Routing Problem
HLC	horizontal logistics cooperation
LSP	Logistics Service Provider
PLOP	Partner level Optimisation Problem
SVRP	Selective Vehicle Routing Problem

TSP	Travelling Salesman Problem
TSPSTW	Travelling Salesman Problem with soft time windows
COLTSPSTW	Collaborative Travelling Salesman Problem with soft time windows
VMI	Vendor Managed Inventory
VNS	Variable Neighbourhood Search
VRP	Vehicle Routing Problem

Curriculum Vitae

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Current Research

"Route Optimisation in warehouse operations."
The main objective of this research is to develop state-of-the-art scheduling and routing algorithms for transport optimisation in a warehouse environment. In contrast to the existing research on warehouse operations, our goal is to rely heavily on the knowledge available in the vehicle routing research literature.

Research interests and specialities: Vehicle routing, horizontal cooperation in logistics, warehouse automation, robot motion planning, (meta)heuristic algorithms.

Education

2012–2017	**PhD Researcher in Applied economics *(University of Antwerp)*** *"Models for operational optimisation in a horizontal logistic cooperation. Gain sharing, incentives and multi-level objectives."* The main goal of my PhD was to develop solution methods and algorithms for solving collaborative vehicle routing problems. We looked at facilitating the decision-making in a horizontal logistic cooperation, where multiple partners aim at jointly organizing and optimizing their logistic activities. Besides the construction of optimal shared routes, we look at the optimal coalition configuration, the inclusion of a fair cost allocation approach and developed optimisation models in which individual partner interests could be integrated in the logistic optimisation problem. *Grants: FWO fellowship* *Supervisor: Prof. dr. Kenneth Sörensen*
2010–2012	**Msc in Business engineering *(University of Antwerp)*** Production management & Research methodology Thesis on "Profit estimation in a horizontal logistic cooperation"
2007–2010	**Bsc in Business engineering *(University of Antwerp)***

Additional courses

2013	**VRP2013 // Spring school on the Vehicle Routing Problem** Prof. D. Vigo, Prof. C. Prins, Prof. D. Feillet, Prof. M. Gendreau & Prof. V. Pillac Institute of Applied Mathematics (IMA), Université Catholique de l'Ouest, Angers, France
2013	**Advanced optimisation techniques** Prof. K. Sörensen University of Antwerp, Belgium
2012	**Combinatorial optimisation and local search techniques** Prof. J. Beliën KU Leuven, Belgium

List of Publications

In review

Christof Defryn, Kenneth Sörensen, and Wout Dullaert (2017). "Integrating partner objectives in horizontal logistic optimisation models." In: in review

Christof Defryn and Kenneth Sörensen (2017b). "Models for multi-objective optimisation in a horizontal logistic cooperation." In: in review

International peer-reviewed journals

2017 Christof Defryn and Kenneth Sörensen (2017a). "A fast two-level variable neighborhood search heuristic for the clustered vehicle routing problem." In: *Computers & Operations Research* 83, pp. 78–94

2016 Christof Defryn, Kenneth Sörensen, and Trijntje Cornelissens (2016). "The selective vehicle routing problem in a collaborative environment." In: *European Journal of Operational Research* 250.2, pp. 400 –411

Book chapters

2016 Christof Defryn, Christine Vanovermeire, and Kenneth Sörensen (2015). "Gain Sharing in Horizontal Logistic Co-operation: A Case Study in the Fresh Fruit and Vegetables Sector." In: *Sustainable Logistics and Supply Chains*. Ed. by Meng Lu and Joost De Bock. Contributions to Management Science. Springer International Publishing, pp. 75–89

Research papers

2015 Christof Defryn, Kenneth Sörensen, and Trijntje Cornelissens (2015). *The selective vehicle routing problem in a collaborative environment*. Tech. rep. University of Antwerp

2015 Christof Defryn and Kenneth Sörensen (2015d). *A two-level Variable Neighbourhood Search for the Euclidean Clustered Vehicle Routing Problem*. Tech. rep. University of Antwerp

2014 Christof Defryn and Kenneth Sörensen (2014). *Gain sharing in horizontal logistic collaboration – a case study in the fresh fruit and vegetables sector*. Tech. rep. University of Antwerp

Conference presentations

2017 Christof Defryn, Kenneth Sörensen, and Wout Dullaert (2017). "Horizontal logistic cooperations. Integration of individual partner objectives in multi-partner logistic optimisation models." In: *ORBEL31: 31st Annual Conference of the Belgian Operations Research Society*. Brussels, Belgium

2016 Christof Defryn and Kenneth Sörensen (2016b). "Horizontal cooperation in a clustered distribution environment. Exchanging zones for increased efficiency." In: *VEROLOG2016: Annual workshop of the EURO working group on Vehicle Routing and Logistics optimization*. Nantes, France

2016 Christof Defryn and Kenneth Sörensen (2016a). "Horizontal cooperation in a clustered distribution environment. Exchanging zones for increased efficiency." In: *ORBEL30: 30th Annual Conference of the Belgian Operations Research Society*. Louvain-La-Neuve, Belgium

2015 Christof Defryn and Kenneth Sörensen (2015a). "A multi-objective collaborative approach for the Travelling Salesman Problem with Time Windows." In: *EURO2015: European Conference on Operational Research*. Glasgow, UK

2015 Christof Defryn and Kenneth Sörensen (2015b). “A multi-objective collaborative approach for the Vehicle Routing Problem with Time Windows.” In: *VeRoLoG2015: EURO Working Group on Vehicle Routing and Logistics Optimization*. Vienna, Austria

2014 Christof Defryn, Kenneth Sörensen, and Trijntje Cornelissens (2014). “The Selective Vehicle Routing Problem in a collaborative environment.” In: *ALIO-EURO conference*. Montevideo, Uruguay

2014 Christof Defryn and Kenneth Sörensen (2014a). “The clustered vehicle routing problem: a two-level variable neighbourhood search.” In: *EURO/IFORS conference*. Barcelona, Spain

2014 Christof Defryn and Kenneth Sörensen (2014b). “The clustered vehicle routing problem: a variable neighbourhood metaheuristic.” In: *15th EU/ME workshop*. Istanbul, Turkey

2014 Christof Defryn and Kenneth Sörensen (2014c). “The collaborative selective vehicle routing problem: vehicle routing in a collaborative environment.” In: *ORBEL28: 28th Annual Conference of the Belgian Operations Research Society*. Mons, Belgium

2013 Christof Defryn and Kenneth Sörensen (2013). “The collaborative team orienteering problem (poster).” In: *VRP2013: European spring school on vehicle routing*. Angers, France

2013 Christof Defryn, Christine Vanovermeire, and Kenneth Sörensen (2013). “The effect of customer characteristics on coalition gains in collaborative vehicle routing.” In: *ORBEL27: 27th Annual Conference of the Belgian Operations Research Society*. Kortrijk, Belgium

Seminar presentations

2014 Christof Defryn (2014b). *The Selective Vehicle Routing Problem in a collaborative environment*. ANT/OR seminar, University of Antwerp

2013 Christof Defryn (2013). *The collaborative team orienteering problem – solving a single-objective collaborative vehicle routing problem*. Doctoral day, University of Antwerp

Business presentations

2014 | Christof Defryn (2014a). *The cost allocation game in practice – What can Shapley do for me?*

Journal Editor

- Open Mathematics – Topical issue on metaheuristics: methods and applications

Ad hoc reviewing

International journals

- RAIRO Operations Research
- Transportation Research: part E
- EJOR // European Journal of Operational Research
- Computers & Industrial Engineering
- Resources, conservation & recycling

Conferences

- EWGT // Euro Working Group on Transportation
- ORBEL29 // Annual conference of the Belgian Operational Research Society
- EU/ME2016 // Workshop on Design and Analysis of Metaheuristics

Teaching experience

Courses

2014–today	**Project management** Msc in Business engineering (University of Antwerp)
2012–today	**Project MVO** Msc in Business engineering (University of Antwerp)

Guest lectures

2015, 2016	**Optimisation in logistics** Msc in Business engineering (University of Antwerp)
2015, 2016	**Advanced supply chain management** Msc in Business engineering (University of Antwerp)

Supervised dissertations

Master dissertations

2016–2017	Jolan De Schutter. *Horizontal logistic cooperation and inventory management.* Faculty of applied economics, Antwerp
2016–2017	Wouter Spiessens. *Partner selection in horizontal logistic cooperation.* Faculty of applied economics, Antwerp
2015–2016	Julie Pollet and Julie Van Den Bogeart. *Horizontal collaborations in logistics.* Key performance indicators for partner selection in shipper collaborations. Faculty of applied economics, Antwerp
2015–2016	David Verbiest and Jeroen Lambrechts. *Solving the feature selection problem using metaheuristics.* Faculty of applied economics, Antwerp
2015–2016	Amitkumar Vaghasiya. *Introducing horizontal collaboration and gain sharing concepts to increase efficiency in transport and logistics in Dubai and Abu Dhabi.* Institute of transport and maritime management, Antwerp

Bachelor dissertations

2016–2017	Iselle De Beuckeleer, Laura Comhaire and Louise Versavel. *Opportunities for logistics in smart cities.* Faculty of applied economics, Antwerp
2016–2017	Aschwin Bauwens, Alexander Jacobs and Toon Keulemans. *Opportunities for logistics in smart cities.* Faculty of applied economics, Antwerp
2013–2014	Arno Reynders, Louis Gabriels and Maxime Krug. *Recent advances in logistics.* Faculty of applied economics, Antwerp

Academic organizational activities

2015	**ORBEL29 // Annual conference of the Belgian Operational Research Society** University of Antwerp, Belgium
2016	**EU/ME2016 // Workshop on Design and Analysis of Metaheuristics** University of Antwerp, Belgium

References

- Prof. dr. Kenneth Sörensen
  Professor Sörensen was my direct supervisor and promotor during my doctoral research at the University of Antwerp.
  e-mail: kenneth.sorensen@uantwerpen.be

- Prof. dr. Trijntje Cornelissens
  Professor Cornelissens was chair of my evaluation commision and chair of my doctoral jury. Furthermore, I acted multiple times as a guest lecturer in her courses.
  e-mail: trijntje.cornelissens@uantwerpen.be

- Prof. dr. Wout Dullaert
  Together with Wout, I worked on collaborative vehicle routing problems. Our joint research resulted in a paper, entitled "Integrating partner objectives in horizontal logistic optimisation models".
  e-mail: wout.dullaert@vu.nl

hobbies and interests

- Music, acting & singing (as choir director, musical teacher, ...)

Colophon

This document was typeset in LaTeX using the typographical look-and-feel `classicthesis`. Most of the graphics in this thesis are generated using `pgfplots` and `pgf/tikz`. The bibliography is typeset using `biblatex`.